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BEHAVIORAL SEGMENTATION OF CUSTOMERS: RFM MODEL AND K-MEANS APPLICATION

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ABSTRACT
The demand for building sustainable customer-company relationships within the context of fierce competition is increasing, in which lingerie is no exception. Segmentation is one of the methods to help businesses build long-term relationships with customers. The main goal of this study is to propose a customer segmentation approach based on RFM (recency, frequency, and monetary) model and K-means algorithm, and then use the one-way ANOVA test to explore the difference in recency, frequency, and monetary attributes in customers of different ages. Data was collected from transactions of 5,280 customers at a lingerie brand store in Vietnam. The results showed that customers are classified into three clusters: loyal customers, irregular low-end customers, and potentially loyal customers. Older customers spend the highest sums of money on lingerie products and the longest time since their last interaction with a company while young customers have the highest purchase frequency. This article contributes to the lingerie industry by providing possible explanations for the behavior of customers from different age groups. It also contributes to the establishment of a suitable method for customer segmentation.

KEY WORDS
Cluster analysis, customer behavior, customer relationship management, marketing strategies, purchase frequency, sustainable relationships.

Currently, the lingerie market size in Vietnam has considerably great growth potential, with about 60 million people using lingerie out of a population of 90 million. Total market revenue is up to 36,000 billion VND with 60%, 35%, and 15% belonging to the low-end, mid-end, and high-end segments, respectively. Vietnamese enterprises have only dominated the mid-end segment, while the high-end and low-end segments belong to foreign enterprises and floating products from China (Ha, 2015). In addition, Vietnamese businesses do not have the brand power of foreign brands, nor the advantage of the low cost of production enjoyed by Chinese products sold in traditional markets. Although the market has great potential, domestic lingerie manufacturing and trading enterprises still face big challenges.

The competition in today's market is increasingly fierce when businesses can create products of equal quality. Business marketing allows a company to broaden its customer reach. However, having an effective marketing campaign is not easy, especially in the context that consumer behavior has changed significantly in recent years. By using data analytics to collect information on customers, a business can better inform its marketing department of the people it should be targeting for its marketing campaigns. In other words, the customers' collected data will be used by stores to propose rational and efficient customer care strategies (Brink & Berndt, 2009). Target marketing breaks down the market into customer segments whose needs and desires are most relevant to the company's goods or services, and then concentrates marketing efforts on one or a few of these segments.

Customer segmentation is becoming a more important part of a successful marketing strategy that may be the difference-maker for businesses in fiercely competitive markets. Customer segmentation can assist companies in maintaining long-term customer relationships and adding clarity to the marketing planning process (Dibb, 1998). There are many methods and variables recommended for customer segmentation. The most popular method is data clustering, which extensively uses recency, frequency, and monetary variables of the RFM model (Punj & Stewart, 1983). RFM is a useful model for investigating a company's customer data set to target its most valuable customers and identify which ones they should focus on (Lumsden, Beldona, & Morrison, 2008). Studies have confirmed that this model's attributes are popular and useful for behavior analysis and customer segmentation (Bauer, 1988; Chan, 2008; Newell, 1997).

Consumer behavior considers consumers' purchase choice, the reason for such choice, and the time and place of purchase. Many theories of buying behavior and its components have been discovered. Social, cultural, psychological, and personal characteristics are considered to shape an individual's consumption behavior. In terms of personal characteristics, key influential factors include age and life-cycle stage, finance, profession, style of living, and personality and self-concept (Kotler et al., 2012). For instance, research indicates that tastes in clothing are usually related to age (Kotler & Armstrong, 2010). According to Amy-Chinn, Jantzen, and Østergaard (2006), age is the key factor in determining women's underwear purchase habits. Tsarenko and Strizhakova (2015) showed that the mediation effect of hedonic consumption is more common among younger consumers while older consumers prefer to interact with store personnel. Hence, understanding the impact of age on purchasing behavior would help managers have business strategies that satisfy their customers.

Vietnamese lingerie businesses need to improve their customer relationship management and develop appropriate marketing strategies to strengthen customer loyalty and improve customer satisfaction. In addition, there are very few studies on lingerie consumption behavior and the overall lingerie industry in Vietnam. Up to now, there have been no studies analyzing the data of lingerie businesses in Vietnam to implement customer segmentation and appropriate marketing strategies. Therefore, this study concentrates on segmenting female customers at a lingerie company in Vietnam based on customers' purchasing behavior. To achieve this goal, the author used the combination of the K-means algorithm and the RFM model to analyze transaction data and customer information (recent purchase time, number of purchases, amount paid, and customer's age) from August 1, 2018 to June 30, 2021.

Objective 1. To propose a customer segmentation model based on the RFM model and K-means algorithm for a lingerie business in Vietnam.

Objective 2. To discover the effects of customers' age differences on recency, frequency, and monetary attributes.

This study first showed an overview of literature related to research content followed by the research methodology. The results and discussions then provided a detailed analysis of the data after the customer segmentation groups were formed. Finally, the conclusion and discussion summarized the research findings, proposed strategies for different customer groups, and outlined limitations and future research.

LITERATURE REVIEW

Customer Relationship Management (CRM). Customer Relationship Management (CRM) began to develop in the 1990s (Jafari Momtaz, Alizadeh, & Sharif Vaghefi, 2013) and was additionally one of the most interesting subjects for scientists (Srinivasan & Moorman, 2005). CRM combines four key components (information, people, process, and technology)

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to manage a customer's relationship with a business (service, support, sales, and marketing) throughout the customer lifecycle and provide customers with a consistent and satisfying range of curated and personalized experiences to foster loyalty (Kincaid, 2003).

Companies are progressively mindful of the numerous advantages of CRM: (1) creating value for the customer, (2) customizing products and services, (3) lower processes, and higher quality products and services, (4) increasing customer retention, loyalty, and profitability (Stone, Woodcock, & Wilson, 1996). Moreover, CRM enables businesses to recognize their most important customers and allocate resources more effectively to retain profitable customers and understand their profitability (Hawkes, 2000), develop deeper and more meaningful connections with customers to maximize the long-term value of customers for the business (Peppers, Rogers, & Dorf, 1999), comprehend and impact customer behavior through effective communication to further enhance customer retention, customer acquisition, and customer loyalty (Swift, 2001).

Customer Segmentation. Customer segmentation, first introduced by Smith (1956), is a key player in CRM. Customer segmentation is the partition of all customers into, smaller groups made up of customers with comparable necessities and characteristics (Dibb, 1998; Güçdemir & Selim, 2015; Smith, 1956). Many businesses have tried to quantify and capitalize on customer value in order to realize the full potential of their consumers (Gloy, Akridge, & Preckel, 1997; Verhoef & Donkers, 2001). Customer segmentation can thus allow companies to develop and implement various strategies to maximize the value of customers. Market segmentation is divided into four categories: demographics, geography, psychology, and behavior (Armstrong & Kotler, 2005). Many marketers believe that the greatest points to start when conducting market segments are behavioral variables such as benefits, loyalty status, occasions, buyer-readiness stage, user status, usage rate, and attitude toward products and services (Cleveland, Papadopoulos, & Laroche, 2011; Kotler & Keller, 2008). Behavioral segmentation is often based on past customer behavior (Machauer & Morgner, 2001). With the development of technology, behavioral segmentation is becoming more and more popular lately.

K-means Clustering. Clustering is one of the most useful segmentation techniques for identifying homogeneous clusters of customers and creating particular marketing tactics (Liu & Shih, 2005). A cluster is a group of data that are distinct from the items in other clusters but have properties in common with one another within the same cluster (Han, Pei, & Kamber, 2012; Hosseini, Maleki, & Gholamian, 2010). The technique of clustering is popular in many business applications, including customer segmentation, customer profitability, statistical data analysis, and data mining among others.

The K-means algorithm, originally proposed by MacQueen (1967), has become a vital clustering algorithm (Han et al., 2012). The mean value of the objects in a cluster is represented by a cluster center (García, Luengo, & Herrera, 2015). When using K-means clustering, the intra-cluster dissimilarity is determined by summing all the distances between the objects and the cluster center (Li, Deogun, Spaulding, & Shuart, 2004).

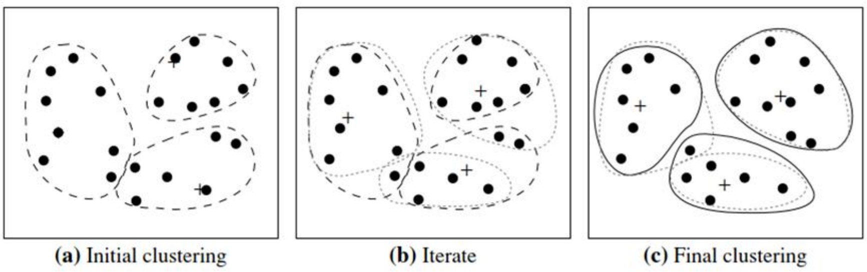

Figure 1 – Clustering of a set of objects using the K-means clustering (Han et al., 2012)

The K-means clustering procedure was summarized as follows (Han et al., 2012):

- Step 1. Randomly select the number of clusters (k) of the objects as the initial cluster centers from a data set containing n objects;

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- Step 2. Repeat;
- Step 3. (Re)assign each object to the cluster to which the object is the most similar, based on the mean value of the objects in the cluster;
- Step 4. Update the cluster means, that is, calculate the mean value of the objects for each cluster;
- Step 5. Repeat steps 3 to 5 until no change.

RFM (recency - frequency - monetary) Model. RFM (recency - frequency - monetary) was first introduced by Huges in 1994 (Huges, 1994; Nikaein & Abedin, 2021), which is by far the most effective and straightforward CRM implementation approach (Cheng & Chen, 2009), widely used for understanding customer buying behavior (Bauer, 1988; Chan, 2008), and often utilized in direct marketing for segmentation (Bult & Wansbeek, 1995). RFM model analyzes the buying behavior of customers by examining when a customer makes a purchase, how often they purchase, and how much they buy in a certain period (Wei, Lin, & Wu, 2010).

Specific attributes (recency, frequency, and monetary) in RFM model play an important role in capturing customers' buying activity (Tsai & Chiu, 2004). Recency measures the interval between the date of the customer's most recent purchase and the end of the statistical cycle. Days are frequently used as a unit of measurement in recency. Customers who are inactive and have made a long-ago purchase have a high recency value while customers who have recently purchased have a low recency value. The lower the recency value, the closer the time from the last purchase to the present time, and the higher the likelihood of customers making a purchase soon (Bult & Wansbeek, 1995).

Frequency describes the number of transactions in a particular period. Customers who often go shopping would have a high-frequency value, whereas customers who rarely visit the store would have a low-frequency value. The larger the frequency value, the greater the chance that customers will place new orders (Wu & Lin, 2005). Moreover, the higher the frequency of customer purchases, the higher the customer loyalty (Bult & Wansbeek, 1995).

Monetary refers to the total amount of money spent by a customer on goods or services in a given period. The more money customers spend on the business, the greater the monetary value recorded. Customers are more likely to repurchase a company's goods or services when the monetary value is high (Wu & Lin, 2005). Wu et al. (2020) also indicated that the more money spent, the more loyal consumers are.

Previous Studies. Scholars have tried to understand the behavior of men versus women while buying apparel. According to Hourigan and Bougoure (2012), women were found to be more fashion and image-conscious. In addition, women are more likely to be evaluated based on their physical looks (Locher, Unger, Sociedade, & Wahl, 1993). Therefore, women are more interested in fashion than men are, and one of the indispensable fashion items for women today is lingerie.

Lingerie has a social significance for women and serves as a means of personality expression (Gibbins & Gwynn, 1975). Lingerie for women is aptly characterized as a high-involvement product because it involves a perceived risk based on the likelihood of a mis-purchase, the pleasure it brings to its users and the symbolic value through which it gives the user a sense of self-concept (Aagerup, 2011; Hart & Dewsnap, 2001; Peters, Shelton, & Thomas, 2011). According to Debbie Risius, Thelwell, Wagstaff, and Scurr (2012), a good bra has the power to boost self-confidence by "changing the views of one's body" which indicate the impact of psychological factors on the perceived performance of a bra.

Although lingerie is also a fashion item, previous authors demonstrated that it cannot be considered a simple purchase of clothing because the decision to buy a bra depends on many interconnected factors, including physiological, psychosocial, functional, and economic (Hart & Dewsnap, 2001). Lingerie is a particular type of garment that makes people fantasize and feel hedonistic (Filipe, Montagna, & Carvalho, 2011; Hume & Mills, 2013). Therefore, it can be said that the consumer's buying motivation for lingerie involves a complex set of dimensions, which is dictated by several choices including lifestyle (Richards & Sturman, 1977), personality and behavior (Attwood, 2005; Haytko & Baker, 2004), self-esteem (Lennon, Rudd, Sloan, & Kim, 1999; Workman & Cho, 2012), confidence (Aagerup, 2011;

Holmlund, Hagman, & Polsa, 2011), and social acceptance (Hogg, Sherman, Dierselhuis, Maitner, & Moffitt, 2007) instead of only its utility (Hart & Dewsnap, 2001; Hume & Mills, 2013). In previous studies, lingerie buyers have been divided into segments according to their level of involvement (Hart & Dewsnap, 2001; Hume & Mills, 2013) and lifestyle (Richards & Sturman, 1977), concentrating on how their attitude and behavioral traits are influenced by their profession, level of education, income, nation, and city of residence.

Customer motivation to buy lingerie depends on many factors. The limited literature research on lingerie has taken behavioral viewpoints and demographics into consideration when segmenting consumers to purchase lingerie. One of the demographic factors that many authors are interested in, not only in the field of fashion but also in many studies on consumer behavior, is age.

According to psychological research, women are generally highly concerned about their physical appearance, which worsens with age (Dittmann-Kohli, 2005). Studies have indicated that female age reflects differences in attitudes toward lingerie (Amy-Chinn et al., 2006; Jantzen, Østergaard, & Vieira, 2016). Women were found to distinguish between clothing options for various age groups, according to Clarke, Griffin, and Maliha (2009), who also noted that women's altered body shape has influenced their decision about color and fashion. Tsarenko and Strizhakova (2015) pointed out that the bra can either cover or show the effects of age on the female physique. D. Risius, Thelwell, Wagstaff, and Scurr (2014) examined the relationship between aging and female breasts and their resulting choice of bra. The results showed that more than half of respondents would no longer wear the bra they used to wear when they were younger, demonstrating a shift in bra preferences with age. In addition, 80% of the women polled said that as they aged, their breasts significantly changed. Aging affects consumer behavior and as a result, regulates female bra purchases in particular (Tsarenko & Strizhakova, 2015).

Most elderly shoppers have different demands for clothing compared to younger ones (Birtwistle & Tsim, 2005; Debbie Risius et al., 2012). Lingerie purchases by women between the ages of 18 and 29 are influenced by social appearance, shopping experience, and self-esteem (Filipe et al., 2011; Koff, Benavage, & Wong, 2001) while women between the ages of 30-44 are highly influenced to buy lingerie to cover their age-related physical appearance to look socially acceptable (Clarke & Korotchenko, 2011; Twigg, 2007). Singh (2018) reported that customers of different age groups and occupations have different purchasing frequencies and amounts of spending on lingerie products within a month. Female students aged 21-25 want to look fashionable but do not have a high disposable income. Housewives from 25-36 years old are conscious of their bodies and do not tend to spend high, they just focus more on the convenient function of the product and the convenience of shopping. Working women, aged 25-36, have clear career orientations and high disposable income hence demand new trendy styles.

Based on previous studies on the differences in shopping behavior of customers of different ages in lingerie, to discover whether there are effects of age differences the recency, frequency, and monetary attributes, the following hypotheses are proposed:

H_1: Customers of different ages have different amounts of time since a customer's last transaction with a company, which means, there are significant differences in recency among customers of different ages.

H_2: Customers of different ages have different numbers of lingerie purchases, which means, there are significant differences in frequency among customers of different ages.

H_3: Customers of different ages spend different amounts on lingerie products, which means, there are significant differences in monetary among customers of different ages.

METHODS OF RESEARCH

This study analyzes the behavior of customers when making purchases at a lingerie company in Vietnam. The company is located in Can Tho city, the largest city in the Western Region and the country's fourth-largest city. This city is now the region's most significant center of economy, culture, science, and technology (Agar, 2006). The company's main business is the retail of lingerie products such as bras, panties, lingerie accessories, nightgowns, pajamas, etc.

This company offers customer membership. Once customers register as members the company has access to their basic information such as customer ID, customer name, gender, and date of birth. However, not all customers agree to register, that is, businesses lack those customers' information. Therefore, the scope of this study is only interested in transactions of registered customers.

The customer data set provided by the lingerie company includes all transactions of 6,914 member customers from August 1, 2018 to June 30, 2021. Table 1 shows the basic information of customers in the study.

Table 1 – Customer basic information

Customer information	Data Type	Description
Customer ID	Text	Automatic customer code
Customer name	Text	Customer's name or nickname
Gender	Text	Customer's gender (Male/Female)
Date of birth	Date	Customer's date of birth in the form of dd/mm/yyyy
Payment time	Date	The specific time for each customer's transaction in the form of dd/mm/yyyy hh:mm:ss AM/PM
Sales	Number	Amount customers pay per transaction. Currency: VND (Vietnamese Dong)

Statistica version 12.0 and SPSS version 24.0 were used for the statistical analysis of the data in the following steps. The research analysis process in the study was conducted according to the following seven steps:

(1) Original data is processed to remove unsatisfactory records;

(2) Satisfactory data was transformed to fit the research model;

(3) Three attributes (recency, frequency, and monetary) value converted to z-score normalization;

(4) K-means algorithm was applied for data clustering;

(5) Cluster naming and cluster analysis were performed based on cluster characteristics;

(6) One-way ANOVA was applied to find the difference in the impact of age on recency, frequency, and monetary;

(7) And finally, recommendations for marketing strategy are suggested.

Data cleaning and data transformation are critical for enhancing the data quality and, subsequently, the data mining outcomes. The data cleaning operations are procedures that fix bad data, remove some inaccurate data from the dataset, and decrease excessive data detail (García et al., 2015). Regarding gender, only 53 customers out of 6,914 were recorded as male. This study only focuses on women given that they contribute the highest proportion of revenue to the lingerie businesses, so all male samples were excluded. Regarding age, only 1.9% (132 people) of customers were over 40 years old and only 4 customers were under 16 years old (0.06%). Therefore, these records were discarded as well. In addition, some records that were found to be incomplete on the customer's date of birth were also removed. In summary, after the unsatisfactory records were eliminated from the study, a total of 5,280 samples were recorded, of which 100% were female and ranged in age from 16-40 years old.

Table 2 – Three attributes of the RFM model and age after transformation

Attributes	Calculation
Recency (R)	The number of days from the last purchase to June 30, 2021.
Frequency (F)	The total number of purchases made within a study period.
Monetary (M)	Total amount spent by the customer in the study period.
Age	Customer's age group, in one of the following age groups: 16-20, 21-25, 26-30, 31-40

Note: The study period was from August 1, 2018 to June 30, 2021.

Data transformation involves transforming or consolidating data into forms suitable for mining (Han et al., 2012). The original data set of customer payment time and amount of each transaction needs to be transformed into the number of days (recency), the number of visits (frequency), and the amount of money (monetary). In addition, the customer demographic information (age) also needs to be transformed to facilitate subsequent analytical steps. All customers were grouped into 4 batches (16-20, 21-25, 26-30, 31-40) according to their age. The three attributes of the RFM model and age were transformed as described in table 2.

Tables 3 and 4 show an example of a customer's data before and after transformation.

Table 3 – Example of customer transaction data before transformation

Invoice number	Customer ID	Customer name	Gender	Date of birth	Payment time	Sales
HD002743	KH000050	Customer A	Female	1985/01/08	08/03/2019 3:32:26 PM	200,000
HD003804	KH000050	Customer A	Female	1985/01/08	05/08/2020 11:14:08 AM	300,000
HD004643	KH000050	Customer A	Female	1985/01/08	06/21/2021 5:53:52 PM	500,000

Table 4 – Example of customer transaction data after transformation

Customer ID	Customer name	Gender	Age groups	Recency (days)	Frequency (transactions)	Monetary (VND)
KH000050	Customer A	Female	31-40	9	3	1,000,000

The normalization step should be completed before the clustering process to create a dataset prepared for the clustering process. In this study, recency, frequency, and monetary attributes have different units of measurement. The unit of measure of recency is day while that of frequency is visit and that of monetary is currency. Therefore, the data should be normalized to prevent dependence on the use of measurement units (Han et al., 2012). In z-score normalization, the original value v is normalized to v'as shown in eq. (1) (García et al., 2015; Han et al., 2012):

$$v' = \frac{v-\bar{A}}{\sigma_A} \quad (1)$$

Where: v'= z-score normalization (z-score); v = original value; $\bar{A}$= mean of the values of attribute A; σ_A= standard deviation.

Z-score represents the distance between a given measurement v and the mean, expressed in standard deviations (McClave, Benson, & Sincich, 2018). The mean and standard deviation of all the values is 0 and 1, respectively. A z-score value can be negative (raw score < the mean average) or positive (raw score > the mean average). A data point score is equal to the mean score if the z-score is zero. Similarly, a Z-score of 1.0 is equivalent to a value that is one standard deviation above the mean. To facilitate the analysis, original recency, frequency, and monetary value were converted to z-score normalization (ZR, ZF, and ZM).

Customers that behaved similarly were grouped by K-means clustering. K-means algorithm output and cluster quality heavily depend on choosing the appropriate number of clusters (k). There are many indicators for selecting the number of clusters (k), among them, Akaike's information criterion (AIC) is a common model selection criterion (Akaike, 1974). This study performed a K-means clustering analysis with three variables (ZR, ZF, and ZM) and assesses the optimum number of clusters based on AIC.

AIC is used to choose between models with various numbers of parameters (Kodinariya & Makwana, 2013). The addition of a penalty term for each parameter aims to balance the rise in likelihood brought on by the extra parameters (Akaike, 1974). The AIC is calculated as shown in eq. (2):

$$\text{AIC} = 2p - 2\log(L) \quad (2)$$

Where: p is the number of free parameters and L is the log of the likelihood for the model.

While objects in distinct clusters should be dissimilar, those within clusters highly resemble each other (Evans, 2017). According to a distance function, the similarity is typically determined by how close the instances are to one another in space. The diameter of a cluster can be used to determine its quality. An alternate measure for cluster quality is the average distance between each object in the cluster and its centroid (García et al., 2015). However, the most common measurement for distance is the Euclidean distance (Han et al., 2012) which is used in the K-means clustering algorithm to measure object similarity (Agrawal, Faloutsos, & Swami, 1993). The formula for the Euclidean distance between objects i and j (García et al., 2015; Han et al., 2012), as shown in eq. (3):

$$\mathrm{d}(i,j) = \sqrt{(x_{i1} - x_{j1})^2 + (x_{i2} - x_{j2})^2 + \cdots + (x_{ip} - x_{jp})^2} \quad (3)$$

With i = (x_{i1}, x_{i2},..., x_{ip}), j = (x_{j1}, x_{j2},..., x_{jp}) be two objects described by p numeric attributes.

RESULT AND DISCUSSION

Before clustering, the ideal number of clusters (k) as the input of the K-means algorithm was selected using AIC. The variables ZR, ZF, and ZM with the characteristics listed in Table 5 were utilized in AIC statistics.

Table 5 – The characteristics of ZR, ZF, and ZM

	N	Minimum	Maximum	Mean	SD
ZR	5,280	-2.36	2.98	0.00	1.00
ZF	5,280	-0.44	14.33	0.00	1.00
ZM	5,280	-0.84	12.52	0.00	1.00

AIC was calculated with 10 clusters from 1 to 10 and the cluster's results were described in Table 6 and Figure 2.

Table 6 – Auto-clustering

Number of Clusters (k)	Akaike's Information Criterion (AIC)	AIC Change[a]	Ratio of AIC Changes[b]	Ratio of Distance Measures[c]
1	10989.951			
2	6852.334	-4137.617	1.000	2.447
3	5168.751	-1683.584	0.407	1.991
4	4328.940	-839.811	0.203	1.831
5	3875.799	-453.141	0.110	1.499
6	3577.562	-298.237	0.072	1.005
7	3280.729	-296.833	0.072	1.050
8	2998.696	-282.033	0.068	1.345
9	2792.163	-206.533	0.050	1.083
10	2602.362	-189.802	0.046	1.513

[a.] *The changes are from the previous number of clusters in the table.*
[b.] *The ratios of changes are relative to the change for the two cluster solution.*
[c.] *The ratios of distance measures are based on the current number of clusters against the previous number of clusters.*

Figure 2 showed that among 10 clusters, the value of AIC from clusters 3 to clusters 5 did not change significantly, so clusters 3, 4, or 5 are potentially good options. In Table 6, of the three solutions in terms of the number of clusters (k = 3,4,5), the solution with k = 3 has the highest ratio of distance measures. Therefore, the number of clusters of 3 (k = 3) was the most appropriate in this study.

After choosing k = 3 as input for the K-means algorithm, three clusters were formed. Z-score normalization of recency, frequency, and monetary, which are abbreviated as ZR, ZF, and ZM present the meaning value of recency, frequency, and monetary. Table 7 lists the coordinates and characteristics of the three clusters.

Regarding ZR, cluster 1 has a negative ZR value (-0.55) which suggest that the mean of recency in cluster 1 is less than the mean of recency in sample population, in other words, customers in cluster 1 have made purchases more recently than the sample population has. Similar to cluster 1, cluster 3 also has a negative ZR value (-0.86). Out of the 3 clusters, only

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cluster 2 has a positive ZR value (0.74). Judging by the value, ZR of cluster 2 > cluster 1 > cluster 3 (0.74 > -0.55 > -0.86), therefore, cluster 2 is recorded as having "high recency", followed by cluster 1 with "moderate recency" and cluster 3 with "low recency". However, it should be noted that the greater the frequency and monetary values, the more positive the customer's buying behavior is, while the greater the recency, the more negative the customer's behavior.

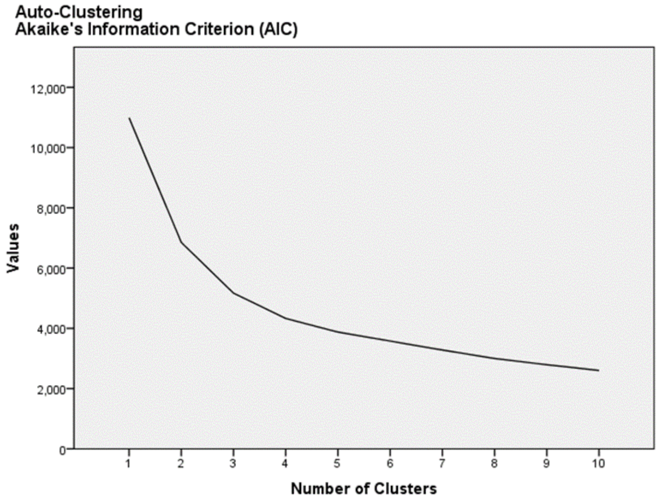

Figure 2 – Determining the number of clusters using AIC

Table 7 – Cluster coordinates and characteristics

Cluster	Cluster 1 (n=354)	Cluster 2 (n=2,777)	Cluster 3 (n=2,149)
Coordinates of center			
ZR	-0.55	0.74	-0.86
ZF	2.72	-0.27	-0.09
ZM	2.59	-0.23	-0.13
Characteristics	Moderate recency High frequency High monetary	High recency Low frequency Low monetary	Low recency Moderate frequency Moderate monetary
Cluster name	Loyal customers	Irregular low-end customers	Potentially loyal customers

In terms of ZF, only cluster 1 has a positive ZF value (2.72) while cluster 2 and cluster 3 have negative values, -0.27 and -0.09, respectively. That is, only customers in cluster 1 have on average more purchases than the average number of purchases in the sample population. The ranking of ZF values is as follows: cluster 1 > cluster 3 > cluster 2 (2.72 > -0.09 > -0.27). Therefore, cluster 1 has "high frequency", cluster 3 has "moderate frequency", and cluster 3 has "low frequency".

Regarding ZM, similar to the ZF value, cluster 1 has the highest ZM value, followed by cluster 3 and cluster 2 (2.59 > -0.13 > -0.23). Among the 3 clusters, only customers in cluster 1 spend more money on average than the sample population, as shown by a positive ZM (2.59) while the ZM of cluster 3 and cluster 2 are negative (-0.13 and - 0.23). Therefore, cluster 1, cluster 3 and cluster 2 are recorded as "high monetary", "moderate monetary", and "low monetary", respectively.

The first cluster has "moderate recency" (ZR = -0.55), "high frequency" (ZF = 2.72), and "high monetary" (ZM = 2.59). This cluster also has the second-best ZR value, which means customers in cluster 1 also visited the store recently. Besides, with the highest ZF and ZM values among the three clusters, customers in cluster 1 are the most regular visitors of the store and spent the most money on the company's products. Repeated purchasing has a positive intention and demonstrates a customer's commitment to a certain brand (Oliver, 1999). Thus cluster 1 customers brought the highest value to the company, with a high level of loyalty and repeat purchase frequency. According to Dick and Basu (1994), those with a high rate of repeat purchases and a positive attitude are loyal customers. Therefore, this cluster was named "loyal customers".

The second cluster has high recency (ZR = 0.74), low frequency, and low monetary (ZF = -0.27, ZM = -0.23) values. Customers in this cluster spent little money on products, rarely visited the store, and have not visited the store for a long time. The likelihood of these customers leaving the business in the future is extremely high, in other words, they only have a tenuous connection to the company and are willing to hunt for a better deal if deals from competitors are more attractive. Hence, this cluster was named "irregular low-end customers".

The third cluster has low recency (ZR = -0.86), moderate frequency, and monetary value (ZF = -0.01, ZM = -0.13). Although these customers do not buy as much and do not visit the store as often as customers in cluster 1, these customers are willing to spend on products and visit the store quite often. Furthermore, customers in cluster 3 have the lowest ZR value, which means that the period since their last purchase is the lowest among the 3 clusters. In comparison to customers who have not visited the company for a long time, customers who have purchased from the company more recently are more likely to decide to do so again for future purchases. With good buying potential as analyzed above, these customers were named "potentially loyal customers".

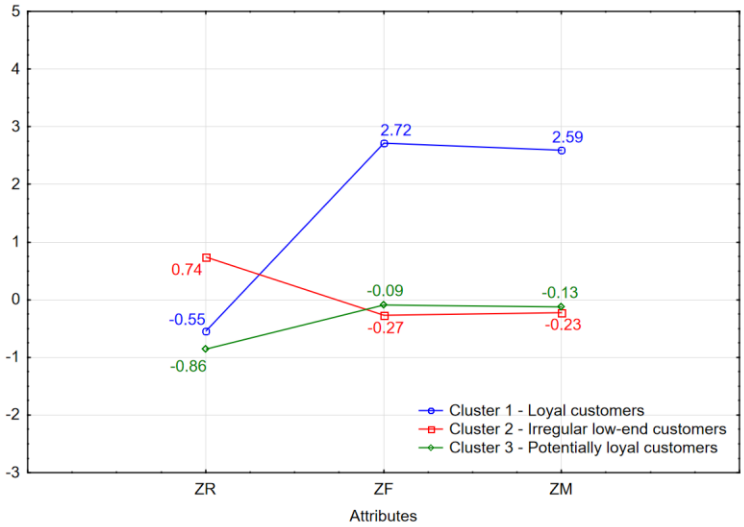

Figure 3 – Plot of means for each cluster

The mean of each cluster was displayed in Figure 3. Regarding cluster 1, the mean value of ZF and ZM are superior to the other two clusters. In contrast, the difference in the mean value of ZF and ZM in cluster 2 and cluster 3 is not big. These two clusters are easily distinguished by ZR because the mean value of ZR in cluster 2 is much higher than that of cluster 3. In general, the highest frequency and monetary values are the two characteristics of cluster 1, while cluster 2 and cluster 3 differ in recency.

The 3D scatterplot that depicts each cluster's coordinates is introduced in Figure 4. The axis represents ZR, ZF, and ZM. The circles illustrated the number of members in each cluster, therefore, the larger the number of customers, the larger the circle. Among the three clusters, cluster 2 accounted for the highest proportion (n = 2,777; 52.6%), followed by cluster 3 (n = 2,149; 40.7%) and cluster 1 (n = 354; 6.7%).

Table 8 shows the characteristics of recency, frequency, and monetary of each cluster and table 9 shows the descriptions of the number of customers and total sales during the study period.

Loyal customers visited the store an average of 6.34 times, which is 3.6 times higher than the sample mean. Moreover, loyal customers spent a very high amount (1,259,886 VND) compared to other customers, which is four times higher than the sample mean.

Interestingly, their lowest total spending amount was 175,000 VND, which outperformed those of irregular low-end customers and potentially loyal customers (9,000 and 10,000 VND, respectively). In fact, with only 6.70% of the company's total customers, loyal customers contributed 26.80% of total sales. This is consistent with the 80/20 rule which states that 80% of revenues are generated by 20% of valuable customers while 80% of costs are produced by 20% of unprofitable customers (Duboff, 1992; Gloy et al., 1997). Indeed, loyal customers bring large sales to the company even though the number of these customers is not large.

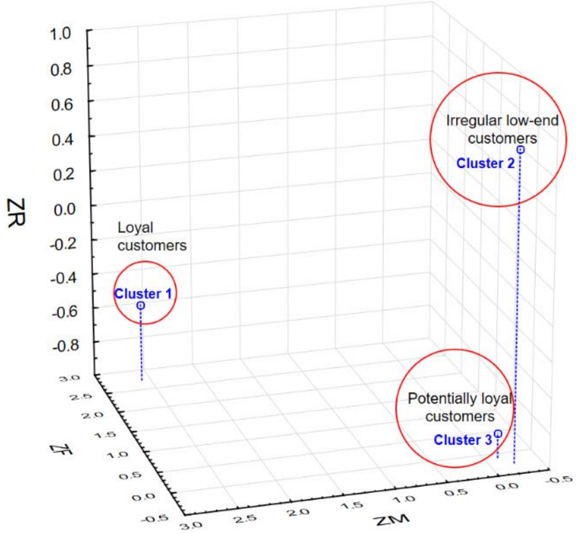

Figure 4 – Three-dimensional scatterplot of three clusters

Table 8 – Descriptive statistics of recency, frequency and monetary of each cluster

	Cluster	Minimum	Maximum	Mean	SD
Recency (day)	1	0	1,043	359.34	193.17
	2	457	1,060	614.60	122.26
	3	1	492	297.66	112.24
	Total	0	1,060	468.49	198.47
Frequency (time)	1	1	26	6.34	3.46
	2	1	5	1.27	0.61
	3	1	6	1.58	0.89
	Total	1	26	1.74	1.69
Monetary (VND)	1	175,000	4,876,600	1,259,886	692,648
	2	9,000	1,456,000	231,580	193,745
	3	10,000	1,265,000	267,587	200,676
	Total	9,000	4,876,600	315,178	364,214

Note: Cluster 1- Loyal customers, Cluster 2 -Irregular low-end customers, Cluster 3- Potentially loyal customers.

Table 9 – Descriptions of the number of customers and sales

Cluster	Customer quantity		Total sales	
	n	%	Sales	%
1	354	6.70%	445,999,749	26.80%
2	2,777	52.60%	643,097,939	38.64%
3	2,149	40.70%	575,046,250	34.56%
Total	5,280	100.00%	1,664,143,938	100.0%

In contrast to loyal customers, irregular low-end customers did make any purchases at the store for a long time, as shown by the recency of 614.6 days. They only bought products 1.27 times and spent an average of 231,580 VND during the period studied in this research. Irregular low-end customers contributed 38.64% of total sales while they accounted for the highest proportion (52.60%) of the total number of customers, which means the number of irregular low-end customers is very large but they contributed just a little over that of potentially loyal customers.

Cluster 3 is the second-largest cluster with 2,149 potentially loyal customers. They spent an average of 267,587 VND and shopped 1.58 times during the study period. While loyal customers and irregular low-end customers have not visited the store in over a year, potentially loyal customers visited the store within less than a year (297.66 days). In a previous study, Western women considered lingerie as a product of fashion and style, while the majority of Indian women saw it only as a functional garment (Singh, 2014). Similar to Indian women, Vietnamese women are also Asian, so most of them also consider lingerie as a functional garment. Hence, they do not often go shopping for lingerie nor would they spend more on lingerie compared to other fashion products.

One-way ANOVA assisted in establishing the differences in customers from five different age groups for different attributes in the RFM model (recency, frequency, and monetary) (Table 10).

Table 10 – The differences among customers from four age groups for ZR, ZF, and ZM

Age groups	16-20 (1)		21-25 (2)		26-30 (3)		31-40 (4)		F	Scheffe's
Variable	Mean	Std	Mean	Std	Mean	Std	Mean	Std		
ZR	-0.42	0.93	-0.00	1.00	0.13	0.97	0.28	1.01	58.25***	(1 < 2 < 3 < 4)
ZF	-0.11	0.83	0.05	1.05	-0.01	1.00	-0.12	0.84	7.17***	(1,4 < 2,3)
ZM	-0.22	0.69	-0.05	0.94	0.17	1.15	0.24	1.24	33.33***	(1 < 2 < 3,4)

*Note: *p < 0.05, **p < 0.01, *** p < 0.001.*

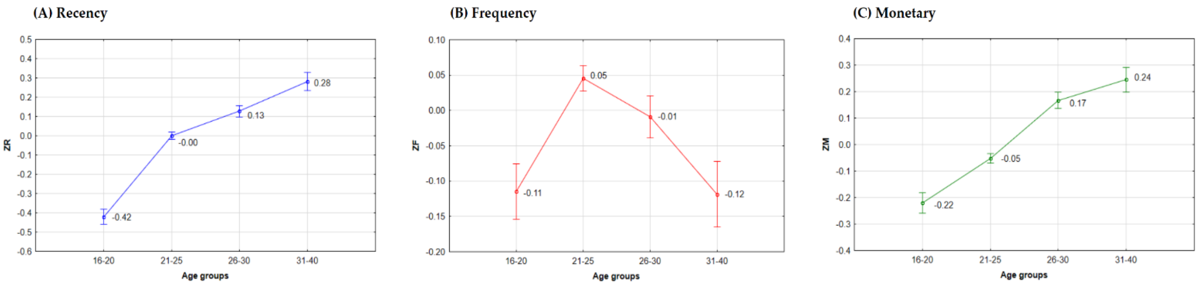

Figure 5 – Z-score by age groups (Note: Vertical bars denote +/- standard errors)

Statistical analysis indicated that there are significant differences in recency, frequency, and monetary among customers of different ages ($F(9, 12836)= 53.224$, $p < 0.001$), therefore, hypotheses H_1, H_2, and H_3 were supported. Post-hoc tests (Scheffe F-test, $p < 0.05$) showed that younger customers have significantly lower ZR and ZM values than older customers, ranked in ascending order from lowest to high are 16-20, 21-25, 26-30, and 31-40 years old, and customers aged 21-30 have a significantly higher ZF value than customers aged 16-20 and 31-40 years old. In terms of recency attribute, younger customers have the shortest time since their last visit to the store while this period for older customers is the longest. It seems that older customers have not visited the store for a long time while the younger customers had visited more recently. Regarding frequency attribute, customers between the ages of 21 and 30 visited the store more often than other customers. Regarding the monetary attribute, older customers spend more money on lingerie products than younger customers.

As shown in figure 6, the blue, red, and green points represent means of ZR, ZF, and ZM, and vertical bars denote +/- standard errors. Customers of the same age but in different clusters have different ZR, ZF, and ZM. Customers in the same cluster but at different ages also have different ZR, ZF, and ZM.

Table 11 shows the distribution of 5,280 customers in each cluster by age group. Customers between the ages of 21 and 25 make up most of the market (57.92%), while those between the ages of 31 and 40 make up the least (8.75%). Regarding the mean of ZR among the three clusters by age groups, potentially loyal customers aged 16-20 years old have the lowest ZR value (-0.99) while irregular low-end customers aged 31-40 years old

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have the highest ZR value (0.84). Regarding the mean value of ZF, loyal customers aged 16-20 years old lead with the highest ZF value (3.16) while irregular low-end customers aged 16-20 years old have the lowest value (-0.32). Regarding the mean value of ZM, loyal customers aged 31-40 had the highest ZM value (3.6) but irregular low-end customers aged 16-20 years old had the lowest value (-0.35).

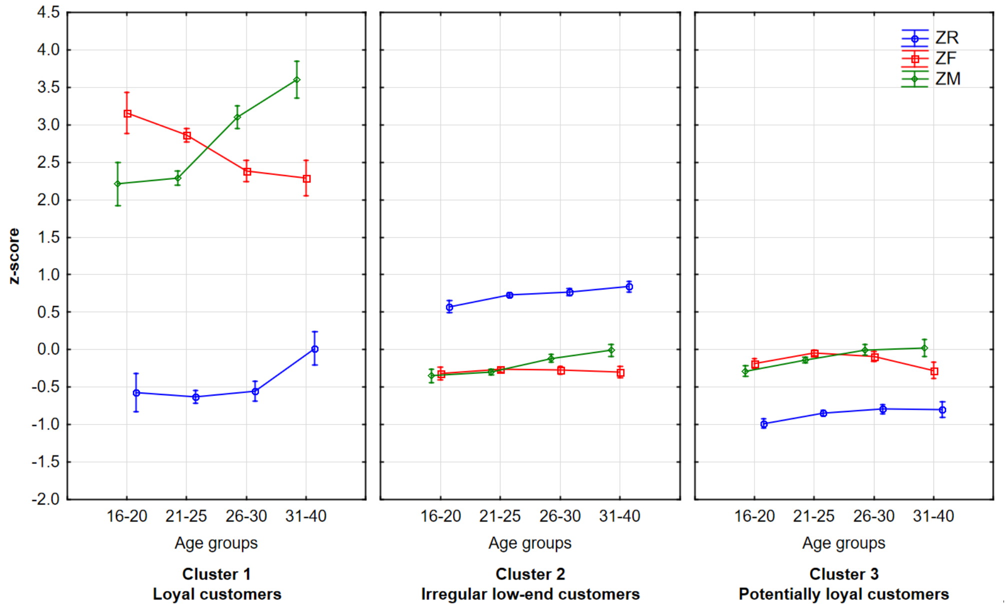

Figure 6 – Z-score of recency, frequency, and monetary by clusters and age groups

Table 11 – Descriptive statistics of three clusters by age

Age groups	Cluster	Number of samples N	%	ZR Mean	SD	ZF Mean	SD	ZM Mean	SD
16-20	1	23	0.44%	-0.57	1.16	3.16	1.96	2.21	1.28
	2	228	4.32%	0.57	0.47	-0.32	0.30	-0.35	0.45
	3	395	7.48%	-0.99	0.57	-0.19	0.47	-0.29	0.46
	Total	646	12.23%	-0.42	0.93	-0.11	0.83	-0.22	0.69
21-25	1	216	4,09%	-0.63	0.96	2.87	2.03	2.29	1.78
	2	1,615	30,59%	0.73	0.61	-0.26	0.37	-0.30	0.47
	3	1,227	23,24%	-0.85	0.57	-0.04	0.55	-0.14	0.55
	Total	3,058	57.92%	-0.00	1.00	0.05	1.05	-0.05	0.94
26-30	1	84	1.59%	-0.55	0.87	2.38	2.18	3.10	1.99
	2	645	12.22%	0.77	0.62	-0.27	0.37	-0.11	0.58
	3	385	7.29%	-0.79	0.54	-0.09	0.53	0.00	0.58
	Total	1,114	21.10%	0.13	0.97	-0.01	1.00	0.17	1.15
31-40	1	31	0.59%	0.02	1.07	2.29	1.75	3.60	2.29
	2	289	5.47%	0.84	0.69	-0.30	0.30	-0.01	0.67
	3	142	2.69%	-0.80	0.48	-0.28	0.34	0.02	0.60
	Total	462	8.75%	0.28	1.01	-0.12	0.84	0.24	1.24
All	1	354	6.70%	-0.55	0.97	2.72	2.05	2.59	1.90
	2	2,777	52.60%	0.74	0.62	-0.27	0.36	-0.23	0.53
	3	2,149	40.70%	-0.86	0.57	-0.09	0.53	-0.13	0.55
	Total	5,280	100.00%	0.00	1.00	0.00	1.00	0.00	1.00

Note: Cluster 1- Loyal customers, Cluster 2 - Irregular low-end customers, Cluster 3- Potentially loyal customers.

For women, shopping is about more than just finding the right product; it is also about having a good time (Tifferet & Herstein, 2012). Enjoyment is associated with consumers increasing their total purchase amount for both young and old women; however, this effect was stronger for younger women (Tsarenko & Strizhakova, 2015). Another study has also demonstrated that shopping addiction usually begins in young adulthood and seems to decrease with age (Andreassen et al., 2015). Therefore, younger customers have recently visited the store and prefer to shop more often than older customers. However, young people spend less than older people because they are still in school or have just started working and their finances are not high or are financially dependent on their families. These are consistent with a study that found that the female gender, younger age, and high family income were all associated with impulsive buying behavior in the fashion industry (Tifferet & Herstein, 2012).

The 31-40-year-old customer group has the lowest ZF and the highest ZM and ZR. They visited the store less often than younger customers, but they spent more, which means that they have more average sales per transaction than the others. The reason for this behavior is that at this age, most of these customers are married. Compared to young customers who are only interested in outerwear but have little investment in lingerie products, married people are more interested in lingerie. Some women take into consideration the likings of their male partners when they shop for lingerie products – and this is especially true in the case of sexier styles that are becoming more and more popular (Amy-Chinn et al., 2006). Their employment status also has an impact on their motivation to buy because they have more disposable income (Cassill & Drake, 1987; Rana & Tirthani, 2012). Older women typically have higher disposable income and show a stronger preference for clothing that emphasizes quality, comfort, functionality, and visual appeal (Banister & Hogg, 2004; Birtwistle & Tsim, 2005). In addition, career-oriented women have a requirement to look trendy and stylish, so they do not mind investing in better lingerie even if its price is high (Singh, 2018).

RECOMMENDATIONS

Customers may be divided into multiple segments based on their value, allowing for the development of marketing plans that are specifically tailored to each group of customers. Based on the characteristics of the three clusters above, business managers can apply different marketing strategies for different customers as follows:

Cluster 1: Loyal customers. Positive buyer-seller relationships, according to Macintosh and Lockshin (1997), are likely to generate purchase intentions or repeated purchase actions. When the connection between customers and the business improves, it can ultimately prompt customer maintenance, loyalty, and profitability. Loyal customers seem to be active, important, loyal, and highly beneficial customers to the company. When a customer has a high monetary value under the RFM model, the business should concentrate more on that customer (Bult & Wansbeek, 1995), so they should be provided with a better quality of service to encourage them to continue their relationship with the company. Enterprises should allocate financial resources, and these customers' human resources should be higher than the other two clusters. Moreover, businesses should pay attention to their feedback, and evaluate the factors that contribute to their loyalty so that they may be applied to other customers. Businesses can increase income by attracting and keeping profitable customers at a low cost (Safari, Safari, & Montazer, 2016). Therefore, managers can maintain relationships with them through incentive programs such as providing VIP cards, and gifts on customers' birthdays. Positive word of mouth will help businesses increase sales. These customers have goodwill with the business, so they can spread word of mouth to introduce new customers to the business. Managers can provide rewards for them to actively promote the company's brand through social media to attract the attention of their relatives and friends, thereby brand awareness will lead to future purchases. It can be said that loyal customers are customers who have experienced the company's products many times, so when preparing to sell a new product or launch a marketing campaign, managers can consult with loyal customers.

Cluster 2: Irregular low-end customers. According to Goodman (1992), the RFM model avoids concentrating on less profitable consumers and allows resources to be directed toward those who were more profitable. It seems that irregular low-end customers do not shop often and have a high probability of not being too interested in the business. However, according to Pfeifer (2005), gaining a new customer is five times more expensive than keeping an existing one. Even when these customers are about to go into inactivity, they have used the company's product before. Instead of spending the budget to find new customers, managers should adopt strategies to reactivate them. Therefore, budgets for

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irregular low-end customers should not be too high, but less expensive and more effective solutions can be considered. For example, by occasionally sending them messages with exceptional offers, managers can remind them of their desire to make a purchase. After a period of monitoring the response behavior of the campaigns, managers can re-filter the objects that have interacted with the campaign and decide to continue or discontinue caring for them based on their willingness to remain or leave the business. Besides, the company should try to determine the reason for their unwillingness to purchase again and address any existing shortcomings.

Cluster 3: Potentially loyal customers. Potentially loyal customers have only recently purchased, so they are more likely to remember the business compared to customers that have not had a transaction for a long time. Potentially loyal customers also have a relatively good level of spending and number of transactions, reflected in the frequency and currency ranked second out of the 3 clusters. Therefore, this group of customers can easily be converted into loyal customers. Marketers should create promotions specifically for these customers to encourage them to increase their spending and return to the store by using sales promotion, cross-selling, or up-selling. In addition, marketing managers should set up a reasonable spending level so that potentially loyal customers can approach and have attractive rewards when they achieve it. Specifically, the level of sales required for these customers to achieve should not be too high, but at least higher than the average of this cluster. Gradually, when customers get used to frequent store visits and repeated purchasing habits, they can become loyal customers of the business.

Recommendations for customers of different age groups. Age is an important factor, so it is necessary to understand customer behavior depending on age differences. Different age groups perceive advertising messages differently. When running advertising content, it is recommended to customize each different advertising message for the targeted age group. Managers can customize different messages to prevent customers from receiving inappropriate messages for their age. By classifying customers, managers can create specific messages suitable for each customer group on essential occasions such as birthdays and holidays. Managers can even create their promotions tailored to the spending and financial capabilities of customers. For customers aged 16-25, managers should stimulate their purchases with low-price products because they love the shopping experience but spend less. Low-price products would attract customers to visit the store and spend more next time, even encouraging them to invite friends to shop to receive promotions through online social events. For customers aged 31-40, managers should regularly remind them to shop and introduce quality products. Since these customers have a stable income, what they care about is product quality, unlike young people who shop for pleasure. In addition, each different age group has different preferences and needs for lingerie products. Enterprises should research products that each age group loves to have a production and business strategy suitable to their demands and resources.

CONCLUSION

Customers are the assets of the company, they not only have different preferences (Hong & Kim, 2012), but also have varied expectations, revenue, and cost configurations. Therefore, they need to be managed according to their needs (Buttle, 2015). From a customer-centric perspective, CRM has been a popular strategy adopted by many businesses. Instead of mass marketing, targeting customer segments will help businesses build more effective communication and promotion strategies. Therefore, it is crucial to determine which consumers the company should prioritize for profitability. In this regard, segmenting customers partially helps businesses solve this question.

For some women, lingerie shopping can be a personal and sensitive topic (Tsarenko & Strizhakova, 2015). “When was the last time you bought lingerie?”, “How many times did you buy lingerie?”, and “How much did you pay for lingerie products?” are questions that can make respondents feel embarrassed when answering directly, leading them to refuse to participate in a survey or give dishonest answers. However, customers may not be honest when answering a sensitive issue in written form, but their behavior is the most honest answer. In this study, three attributes (recency, frequency, and monetary) of the RFM model were calculated based on the transaction that occurred, not on the customer's answer. Therefore, the application of data mining algorithms helps researchers have an objective view and the results have high reliability.

RFM is an easy-to-use technique that reduces purchasing behaviors to a limited set of variables and identifies customer groups composed of members with purchasing patterns. Customers in a Vietnamese lingerie business were segmented based on their three attributes representing different aspects of purchasing behavior (recency, frequency, and monetary) by the K-means clustering technique. The results show that customers are divided into three groups: loyal, irregular low-end, and potentially loyal customers. Loyal customers have the most purchases and spending while irregular low-end customers are the opposite. Sorted by the number of days since the last visit to the store from lowest to highest, are potentially loyal customers, loyal customers, and irregular low-end customers, respectively. In short, the most valuable customer group for this business is loyal customer, followed by potentially loyal customer. Irregular low-end customers, as the name suggests, are the least valuable. The study also showed differences in the purchasing behavior of customers of different age groups in terms of the time of recent purchase, frequency of purchase, and amount of payment. Customers of different ages have different buying behavior. Older people have the longest days since their last purchase, and they are likely to spend more money shopping than younger people. In contrast, older customers are less likely to visit the store while younger customers are highly active.

Each of customer segmentation has different buying behavior and preferences, so it is not effective to allocate the marketing budget to all customers equally. Business managers should apply different marketing and promotion campaigns for different customer clusters and different age groups customers to minimize the waste of resources of the business.

LIMITATION AND FUTURE RESEARCH

Some limitations of this study can be considered for future research. Firstly, this research attempted to examine the impact of age on recency, frequency, and monetary values, however, in addition to age other demographic factors of customers that may influence customer purchases such as occupation, marital status, and education were not included. Therefore, in the future, this study can expand the profile of these segments with additional demographic features. Secondly, this study did not analyze each product group and specific product. Identifying which products are of higher interest in each age group is very helpful for managers in planning appropriate customer marketing strategies. Future studies can examine product categories that appeal to customers of various ages. From there, managers can have appropriate import and marketing plans. In addition, the authors can collect more data on lingerie purchase behavior on other platforms to have a broader analytical view.

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