ASEAN Marketing Journal

Volume 9 | Number 1 Article 5

November 2021

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Recommended Citation
Vanessa, Nesya and Japutra, Arnold (2021) "Contextual Marketing Based on Customer Buying Pattern in Grocery E-Commerce: The Case of Bigbasket.com (India)," *ASEAN Marketing Journal*: Vol. 9 : No. 1 , Article 5.
DOI: 10.21002/amj.v9i1.9286
Available at: https://scholarhub.ui.ac.id/amj/vol9/iss1/5

Contextual Marketing Based on Customer Buying Pattern in Grocery E-Commerce: The Case of Bigbasket.com (India)

Nesya Vanessa and Arnold Japutra***

The objectives of this research are to identify customer purchase behavior, obtain the number of customer clusters, and form customer profile in order to find situation-based customer purchase behavior pattern. From the given data, the RFM method and K-Means clustering are used to identify the customer purchase behavior and profiles. The result of this research showed that the customer clusters are formed differently in every product category based on the RFM value and K-Means clustering. There are also differences in peak hour for each customer cluster. The best time to deliver notifications and personal messages is near the peak hour. Indeed, this matter is useful to create contextual marketing and targeted advertising that is designed based on customer cluster and purchase behavior.

Keywords: Contextual Marketing, Purchase Behavior, Customer Buying Pattern, E-commerce, Grocery E-Commerce, Big Data

Introduction

Technology has fundamentally changed consumer behavior and transformed the way industries work. The connected commerce era has arrived in many industries, especially fast moving consumer goods (FMCG). Nowadays, shoppers are comfortable with the benefits of digital shopping and expect similar experience in grocery industry. The physical and digital worlds are becoming harder to define. People are no longer shopping completely online or offline, instead they are taking a blended approach using whatever channel suits their needs best. The most successful stores and manufacturers will be at the intersection of the physical and virtual worlds. Taking advantage of technology could make shoppers happier and give them freedom whenever and wherever they will shop (Nielsen, 2015). Eagerness to utilize advanced retailing choices is most increased in creating markets in the Asia-Pacific (60%), Latin America (60%), Africa/Middle East districts (59%), and trails in Europe (45%) and North America (52%) (Nielsen, 2015). The increasing number of portable and broadband penetration especially in developing countries, have additionally helped online grocery deals. Asia-Pacific reliably surpasses the worldwide average for online shopping.

In e-commerce, product selection matters. Virtual basket does not really reflect a physical basket. Indeed, the correlation between both virtual and physical basket is frequently a reverse one. As an example, in US, the mix of online product sales is 60% for non-food products and 40% for food products. On the other hand, the product sales in physical stores are 40% and 60% respectively for non-food and food products. It is the exact reverse between in-store and online store (Nielsen, 2015). Nielsen's research regarding "The Future of Grocery" suggested there are four factors that influence e-commerce success based on consumer product selection (Nielsen, 2015): stock-up, price, urgency, and inspection. Both stock-up and price act as the enablers that lead to customer purchase while both urgency and inspection act as the barriers that might hinder customer to purchase product from an e-commerce. In some cases, there are enormous opportunities in niche markets such as healthy foods and rare products. The Nielsen research showed that today's shoppers are more aware about the freshness and naturalness of products which are beneficial.

To analyze and identify the user behavior of an e-commerce, data mining is the appropriate method to dig deeper and find customer insights. The digital trace left by the customer every time they use the e-commerce can be recorded and analyzed. The data mining is useful

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to discover business insights and find the best business strategy. Important connections and causalities are the way to oversee massive information and enabling companies to see more detailed pictures of their costumer behavior. Data mining also discovers the important patterns rapidly, precisely, and with relevance. It gives a much-needed competitive advantage in a high-risk environment by providing insights into customer-buying patterns to guide the product offering, supply chain planning, and execution (Savitz, 2012).

The customer insights derived from big data can enable marketers to design contextual marketing and targeted advertising so that each customer can get the best offering and advertising message based on their dynamic historical behavior. Contextual marketing is a big thing. In digital industries, many customers disregard advertisements such as banner, video, sponsored search if it is not related to their needs or preferences. As marketers, we ought to be able to adapt and focus to create advertisements and campaigns based on context. Digital experience and relevant advertisements are the customer's expectation. Today, contextual marketing is common as the costumers' online behaviors are mostly being tracked. Profile tracker on website browsers and mobile devices are able to know what we search, which website we visit, or where we are located. By using this information, marketers are able to target more accurately to engage customers. Contextual marketing is a way to increase customer's experience by using customized marketing in real-time behavior (Delane, 2016). Moreover, the digital life could be traced by knowing the weather, channel preference, location, business or personal, purchase history, past behavior, device, time of day, and language used.

This research focuses on the implementation of contextual marketing in grocery e-commerce in India. India's grocery market has rapidly grown even though it is still has a small market share. The market share estimated is INR 22,5 trillion (USD 350 billion) and remains as the top 10 of food and grocery market in the world. The market growth is around 10%-12% CAGR between 2010 and 2015. The size of online grocery market is still below 1% of overall food and grocery sales at around INR 40 billion (USD 0.6 billion). However, the growth itself reached 35% CAGR with market penetration around 2.3% (EY, 2015).

Despite of rapid growth, the Indian grocery e-commerce has spent huge marketing costs inefficiently, over and on top of the negative margins. They have paid many famous actors to become their brand ambassadors, advertising on various media especially print and outdoor ads. Some grocery e-commerce players even give an offer to the retailers to keep selling in their e-commerce, which increased their burn rates. On the other hand, Indian users have become smarter; they are discount-hungry and become disloyal users. In order to keep availing the 20 percent discount, people order groceries from 4-5 different mobile numbers they have in the same household. Most e-retailers offer 20 percent discount only on first purchase, usually connected to a mobile number. The discount hungry Indian customers went away as soon as the schemes stop. Besides, the competition is not only between grocery e-commerce but also with the wandering pushcart. None of the apps has yet been able to compete with the wandering pushcart owner, selling fresh veggies in India's neighborhoods. The wandering veggie vendor gives credit, knows customers by their names, and often prepares orders before landing at the doorsteps of his buyers (Julka, 2016).

With the implementation of contextual marketing, grocery e-commerce can analyze the customer behavior and select the most effective marketing strategy and engaging advertising to get a more efficient return on the marketing investment. The previous burn rate of money spent on mass advertising can be allocated directly to online-targeted advertising that is predicted to be more engaging to the customers based on their behavior. The sales promotion strategy can vary from discount, bundling, free item, or referral depends on their previous buying pattern. Furthermore, it also can dynamically change between promotional program and loyalty program depends on the changing pattern of customer. This way, it can limit the abuse of discount hunting from disloyal customers because each user will be offered different promotions while increasing customer loyalty by offering specific loyalty programs to the selected potential customers.

The focus of this research is to find the most suitable and effective contextual marketing for BigBasket based on the customer buying pattern. The more detailed formulation of the problem in this study is expressed as follows:

1. How do we identify customer purchase behavior per product category based on their buying pattern?
2. How many customer clusters are formed per product category and what is the customer profile?
3. Which is the best time to deliver notifications and promotional messages to each customer cluster?

The research objectives are to find the most suitable and effective contextual marketing for BigBasket based on customer buying pattern. The detailed objectives are expressed as follows:

1. To identify customer buying pattern based on RFM analysis, in general, and per product category, in particular.
2. To identify how many customer clusters and customer profile are formed in every product category based on RFM analysis and K-Means clustering.
3. To find time-based customer buying pattern that would help to decide the situation to deliver notifications and promotional messages to each customer cluster.

Literature Review

Grocery E-Commerce

Electronic commerce (E-commerce) is a business platform on telecommunication networks to share information, maintain relationship, and conduct transaction related to business (Vladimir, 1996). E-commerce has been booming recently, but the practice it denotes originated almost half-century ago in the Berlin airlift. It started with the EDI (electronic data interchange) for internal firms, the computer-to-computer exchange of standardized electronic transaction documents. The total transaction for grocery e-commerce platform has reached USD 48 billion a year until June 2016 and the e-commerce market share is 4.4% of all FMCG sales (Kantar Worldpanel, 2016). The FMCG market growth is flat but the e-commerce channel for FMCG is growing 1.6% in the same period (Kantar Worldpanel, 2016).

Big Data Analytics

Big data is data that exceeds the processing capacity of conventional database systems. In today's business, the concept of big data has been analyzed from many points of view and in many studies. IBM as one of the leading company for big data analytics found four aspects of big data analytics: volume, velocity, variety, and veracity (IBM, 2011). Volume is one of the aspects related to the scale of data. The data need to be big and have important knowledge. Velocity is the time needed for the big data to be processed. In big data, timing is important and fast response is needed. Data nowadays can be analyzed in real time and the faster data is processed, the more efficient it is. Variety is related to how the big data can comprise. The data could be in different forms such as structured and unstructured. The data could be from open sources such as social media or internal from the company. Veracity is the uncertainty of data. It is about the quality of the data whether we could trust the used information to make decisions. Big data is needed when the data is too big (volume), moves too fast (velocity), doesn't fit the structure of your database architectures (variety), or with uncertain quality (veracity) in order to gain value from this data (IBM, 2011).

Contextual Marketing

Contextual Marketing is an approach and application of marketing in a specific situation that is contextualized and customized (Carson, Enright, Tregear, Copley, Gilmore, Stokes, Deacon, 2002). There are a few factors that are able to simplify the contextual marketing by using inter-dependent, inter-related and synergistically influences that become an interface between the firm and the market firms (Marvel, 2012). Contextual marketing could be done in online and mobile marketing that provides a customized advertisement based on user information or past user behavior such as recent website browsing. The goal of contextual marketing is to give the user advertisement that represents products and services that they are already interested in (Marvel, 2012).

Targeted Advertising

Targeted advertising is a type of advertising used by online advertisers that utilized refined techniques to the most receptive audiences with specific characteristics, depending on the product or person the advertiser is promoting (Plummer & Rappaport, 2007). Moreover, these characteristics could be in many forms: (1) demographic (race, economic status, sex, age, the level of education, income level, and employment), (2) psychographic (consumer's values, personality, attitudes, opinions, lifestyles, and interests), (3) behavioral variables (browser history, purchase history, and other recent activities). Targeted advertising would be more cost effective since it only focused on certain characteristics and targeted only costumers with high preference to receive the advertisement.

Buying Pattern

Costumer buying behavior is a buying behavior of end costumer for personal consumption and could be individuals or households (Kumar, 2010). Buying pattern shows how costumers purchase goods or services (Kahn, 2012). How the costumers purchase could be shown by frequency, quantity, duration, etc. Buying patterns could also be related to demographic, geographical, and psychological of costumers. Further understanding of buying patterns will give firms benefits for decision making in the field of strategic marketing, segmentation, distribution, and promotion (Kahn, 2012).

RFM (Recency, Frequency, and Monetary)

RFM is the abbreviation of Recency, Frequency and Monetary. RFM method is one of a marketing technique that is used to analyze costumer behavior based on recency, frequency, and monetary (Birant, 2011). Recency refers to how recently a customer has made a purchase and is usually measured by days or time units. Frequency refers to how often the customer purchases. Monetary refers to how much the customer spends and it is shown in currency unit. RFM method is able to show the customers segmentation by dividing the customers into many groups based on the RFM number which will shows the similarity of customer behavior and buying pattern.

K-Means Clustering

The K-means method is a clustering method that choose K center to minimize the average squared distance between each point and its closest center. K-means clustering method is one of the oldest and most important methods in computational geometry. A survey of data mining techniques showed that clustering is the most popular technique that is used in scientific and industrial applications (Berkhin, 2002). Determining the most appropriate number of clusters is assisted by elbow method. The method is a validation and interpretation of the clustering consistency.

Company Profile

The Bigbasket story begins in 1999. The founders are VS Sudhakar, Hari Menon, Vipul Parekh, Abhinay Choudhari, and VS Ramesh. They started their first online shopping business in India called Fabmart.com. They started an online groceries business in 2001 as part of Fabmart. They also succeeded to build an offline store named Fabmall that was a chain of grocery supermarkets in the South of India. In 2006, they sold their business. In 2011, the team got back and launched Bigbasket.com. Bigbasket.com are available in in Bangalore, Hyderabad, Mumbai, Pune, Chennai, Delhi, Noida, Mysore, Coimbatore, Vijayawada-Guntur, Kolkata, Ahmedabad-Gandhinagar, Lucknow-Kanpur, Gurgaon, Vadodara, Visakhapatnam, Surat, Nagpur, Patna, Indore and Chandigarh Tricity. Payment can be processed online using debit or credit card and also by COD (Cash On Delivery).

Bigbasket.com divides their products based on several categories as follows: (1) fruits & vegetable, (2) grocery & staples, (3) bread, dairy & eggs, (4) beverages, (5) branded foods, (6) personal care, (7) household, (8) imported & gourmet, (9) meat. There are also sub-cate-

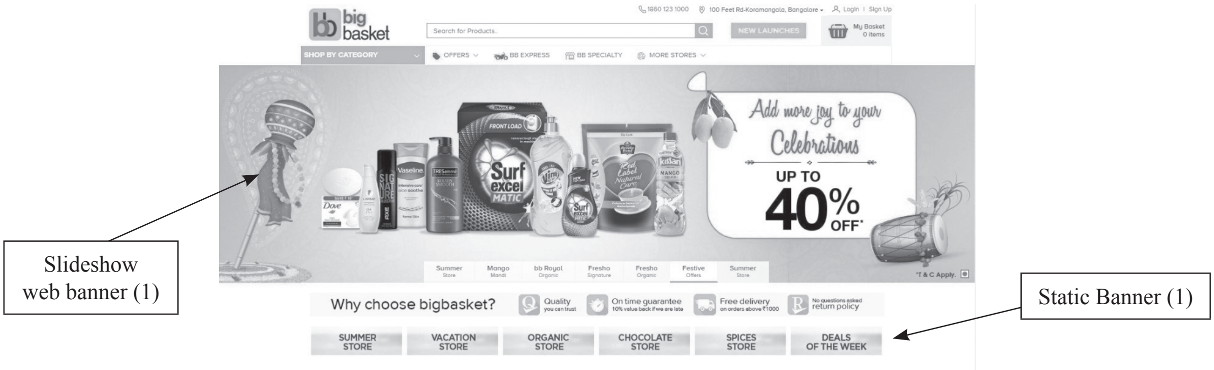

Figure 1. Homepage Banners (www.bigbasket.com)

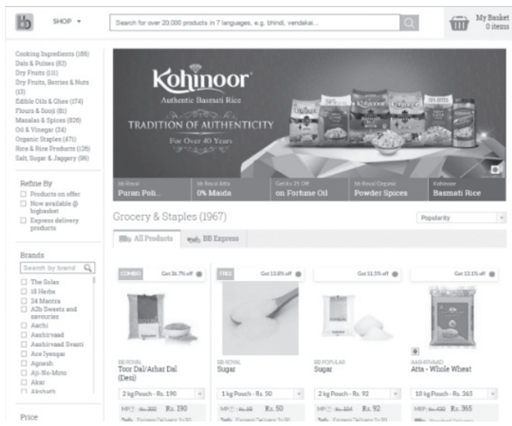

Figure 2. Product Category Banners (www.bigbasket.com)

gory and sub-sub-category in each category. Bigbasket.com set aside some spot in their website page for the advertisement from BigBasket.com itself. It starts from the homepage of BigBasket.com.

There are two types of web banner advertising. First, the slideshow web banner. It consists of promotion such as discount and new products. If the banner is clicked, it will direct customers to the product web page. Secondly, the static web banner. It consists of discount (deals of the week) and products. If the home page is scrolled down, there are still many more banners.

The advertising spot in homepage is different with the advertising spot in each shop category. The only advertising spot is slideshow banner in each product category. There are several advertisements and all the advertisements are related to the category itself.

BigBasket.com also provides a dedicated promotional web page. It consists of discounts, promotions, and bundle packs. BigBasket.com performs email marketing to the customers. There are some clickable parts such as product category that links directly to the website page. There may be more e-mails towards customers that BigBasket.com does as a usual e-commerce. SMS promotion is also available in BigBasket.com. Unfortunately there is no sample from BigBasket.com available in internet. Registration is available using a phone number with India country code. BigBasket.com offers customers to receive notifications via email and SMS.

Methodology

Research Flow

This research is designed to identify the customer profile of Bigbasket.com, an e-groceries in India, based on RFM (Recency, Frequency, Monetary) analysis per product category so that the marketer could devise the most suitable marketing strategy or promotional offer for each distinct customer. Customer segmentation analysis is conducted using K-Means clustering

Table 1. Eight Type of Customer Profile

Cluster	Recency (Days)	Frequency (Times)	Monetary ($)	Customer Profile
C1	High	High	High	Most Valuable Customer
C2	High	High	Low	Barnacle
C3	High	Low	High	Big Basket Shopper
C4	High	Low	Low	First Timer
C5	Low	High	High	Churn Valuable Customer
C6	Low	High	Low	Churn Barnacle
C7	Low	Low	High	Churn Big Basket Shopper
C8	Low	Low	Low	Stranger

Table 2. Variable Descriptions of the Raw Dataset

Variable name	Data type	Description and meaning
Member	Character	Member ID or the unique registered user ID of buyers in BigBasket.com.
Order	Numeric	Order Number or unique Invoice Number ID that is auto-generated for every order checkout that occurred.
SKU	Numeric	Stock Keeping Unit or the product item unique ID.
Created On	Character	Contains the date and time of customer purchase that consists of: year, month, day, hour, and minute of the purchase.
Description	Character	Short description of the product item bought. Every product description is a subset of a subcategory and every subcategory is a subset of product category.

technique. The research flow started with raw data that provided by Magister Manajemen UI (MM-UI). The next step is data pre-processing in order to be able to perform data processing. The data pre-processing starts with data error elimination, followed by the data categorization based on the product description. Date and time also need to be formatted since there are different formats in the raw data. Next, the information regarding hours, days, and months will be extracted from the data. Then, the new dataset based on category are ready to be processed. The dataset will be based on 9 (nine) categories as follows: (1) all categories, (2) beverages, (3) branded foods, (4) bread, dairy, and eggs, (5) fruits and vegetables, (6) grocery and staples, (7) household, (8) meat, and (9) personal care.

The data processing will be using RFM (Recency, Frequency, and Monetary) analysis. Then, the RFM result will be clustered using K-Means clustering to obtain customer segmentation. To distinguish the RFM profile with each other's, the R, F, or M value is examined whether above or below the average value by assigning high (↑) or low (↓). The high or ↑ sign means that the Recency is below the mean value, while the low or ↓ sign means that the Recency is above the mean value. For the recency, the smaller number would be assigned high because of the customer just bought recently. In the other hand, the high or ↑ sign means that the Frequency or Monetary element is above the mean value, while the low or ↓ sign means that the Frequency or Monetary element is below the mean value. The ideal customers have high recency since they just bought the product recently, have high frequency of shopping, and have high monetary value with big amount of spending. So, there will be 8 possible combinations (2x2x2) of customer profiles based on the RFM analysis.

It will also be analyzed based on purchase time. From all the analysis, the contextual marketing design could be formed.

The Raw Data

The raw data used in this study is provided by MM-UI that is obtained from public sales transaction sample data from Big Basket, a leading grocery e-commerce in India. The raw dataset is derived from the Big Basket sales transaction records occurred during 2011-2014 period. It consists of five variables (column) and 62,136 rows.

Data Analysis & Result

The RFM Analysis is performed to all the 9 (nine) dataset. First, we calculated the Recency, Frequency, and Monetary value. The RFM Data is clustered according to their value of Recency, Frequency, and Monetary. The RFM (Recency, Frequency, and Monetary) method needs to be modified to RFQ (Recency, Frequency, Quantity). The quantity assumption is that every row

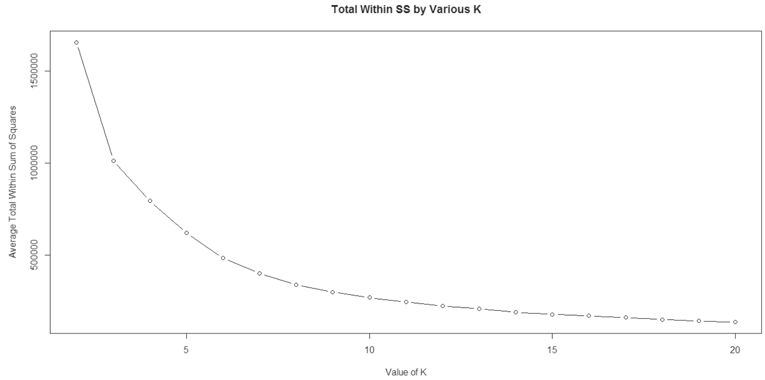

Figure 3. The Curve of k-value and Average Total within SS (all category)

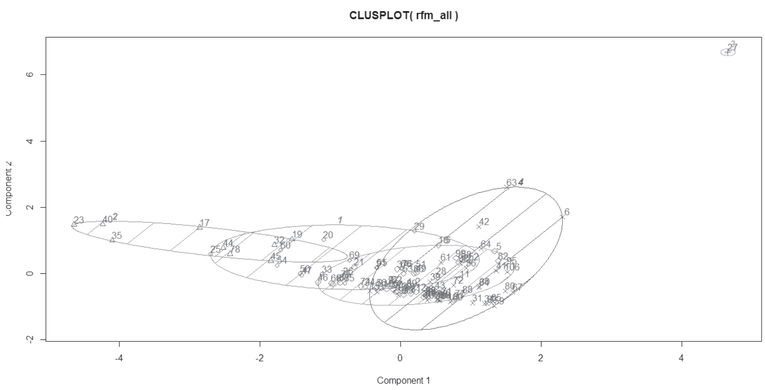

Figure 4. Clusplot All Categories Data

Table 3. K-Mean Clustering Result for All Categories Data

Cluster	Recency (Days)	Frequency (Times)	Monetary (Quantity of Product Item Type)
1	13.16528	130.55556	1105.3333
2	22.68012	89.81818	696.5000
3	18.81093	77.34211	543.8947
4	36.43366	63.11111	437.5000
5	469.14583	24.00000	447.0000

in transaction represents one item bought. If the monetary information is known, it might be more accurate to generate the RFM number. However, the quantity itself is able to represent the monetary value.

The number of cluster is determined following the “elbow” point rule from 19 iterations of K-Means analysis from k=2 to k=20 and each iteration uses the mean value of 100 random within of sum of squares value. After running the K-Means Script, it generated the K-value curve. The number of k (clusters) chosen for K-means analysis is determined from the elbow position on the curve. The iteration of K-means helps us decide the *k* value for clustering. Afterwards, the graphic of k-value and Average Total within Sum of Squares is examined and the result is shown in the figure below, all category products as example.

From the curve in Figure 3, the appropriate elbow point should be k=5. Then, k-means algorithm with k=5 is selected. The R Script executes k-means algorithm with k=5 and is described as follows. The output is shown in the figure below.

The clustering process in Figure 4 is done by K-Means itself. The membership is singular. Each cluster will have different members from the other clusters, no overlaps. The next step is to examine the result of K-means clustering and evaluate each cluster.

Now that each cluster has its RFM value, it should be compared to the mean RFM for all categories data and the output is as shown in table 4.

From the table above, the most recent transaction is in the same day as the last day of transaction from the raw data given. The least re-

Table 4. Mean for All Categories

Description	Recency (Days)	Frequency (Times)	Monetary (Quantity of Product Item Type)
Min. :	0.000	24.00	402.0
Mean :	29.368	79.11	586.2
Max :	469.146	202.00	1438.0

cent transaction happened in 469.14 days ago. The mean of recency is 29.37 days ago which means the customer in average usually made a purchase in every 29.37 days, or almost every month. The least frequent customer purchased 24 times within 4 years but the most frequent customer purchased 202 times within 4 years. The average customer purchase frequency is 79.11 times within 4 years. The least number of product item bought in 4 years was 402 items. The highest number of product item bought in 4 years is 1,438 items. The average monetary is 586.2 items bought within 4 years. The RFM value of each cluster is compared to the mean value, in order to determine whether the RFM value of each is cluster is above average or below average. The data analysis will be performed in all 9 (nine) categories and the results are as follows.

Beverages Category

The RFM data showed that the categories are divided into 3 (three) customer classes as follows: most valuable, first timer, and leaving. There are 40 most valuable members (45.45%), 28 first timer members (31.82%), and 20 leaving customers (22.37%). The beverages category is dominated with valuable customers. The mean recency is 195.2 days ago. The mean frequency is 11.41 within four years. The mean monetary is 13.1 within four years per member.

Branded Food Category

The RFM data showed that the category has 4 (four) customer classes as follows: most valuable, churn, first timer, and leaving. There are 35 most valuable members (33.02%), 12 churn members (11.32%), 20 first timer members (18.87%), and 39 leaving customers (36.79%). The branded food category is dominated with most valuable customers. The mean recency is 65.35 days ago. The mean frequency is 31.62 times within four years. The mean monetary is 64.58 items within four years per member.

Bread, Dairy, and Eggs Category

The RFM data showed that the category has 3 (three) customer classes as follows: most valuable, first timer, and leaving. There are 38 most valuable members (37.62%), 34 first timer members (33.66%), and 29 leaving customers (28.71%). The bread, dairy, and eggs category is dominated by most valuable customers. The mean recency is 148.25 days ago. The mean frequency is 18.3 times within four years. The mean monetary is 24.67 items within four years per member.

Fruits & Vegetables Category

The RFM data showed that the category has 3 (three) customer classes as follows: most valuable, first timer, and leaving. There are 39 most valuable members (36.79%), 65 first timer members (61.32%), and 2 leaving customers (1.89%). The fruits and vegetables category is dominated by first timer members. The mean recency is 63.63 days ago. The mean frequency is 43.83 times within four years. The mean monetary is 243 items within four years per member.

Grocery & Staples Category

The RFM data showed that the category has 3 (three) customer classes as follows: most valuable, first timer, and leaving. There are 29 most valuable members (27.36%), 53 first timer members (50%), and 19 leaving customers (22.64%). The Grocery & Staples category is dominated by first timer members. The mean recency is 36.63 days ago. The mean frequency is 72 times within four years. The mean monetary is 220.4 items within four years per member.

Household

The RFM data showed that the category has 2 (two) customer classes as follows: most valu-

Table 5. Peak Hour in Bigbasket.com Based on Customer Profile

No.	CATEGORY	0-6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1	ALL (MOST VALUABLE)																		
2	ALL (FIRST TIMER)																		
3	ALL (STRANGER)																		
4	BEVERAGES (MOST VALUABLE)																		
5	BEVERAGES (FIRST TIMER)																		
6	BEVERAGES (STRANGER)																		
7	BRANDED FOOD (MOST VALUABLE)																		
8	BRANDED FOOD (CHURN)																		
9	BRANDED FOOD (FIRST TIMER)																		
10	BRANDED FOOD (STRANGER)																		
11	BREAD, DAIRY, EGGS (MOST VALUABLE)																		
12	BREAD, DAIRY, EGGS (FIRST TIMER)																		
13	BREAD, DAIRY, EGGS (STRANGER)																		
14	F&V (MOST VALUABLE)																		
15	F&V (FIRST TIMER)																		
16	F&V (STRANGER)																		
17	G&S (MOST VALUABLE)																		
18	G&S (FIRST TIMER)																		
19	G&S (STRANGER)																		
20	HOUSEHOLD (MOST VALUABLE)																		
21	HOUSEHOLD (FIRST TIMER)																		
22	HOUSEHOLD (STRANGER)																		
23	MEAT (MOST VALUABLE)																		
24	MEAT (STRANGER)																		
25	PERSONAL CARE (MOST VALUABLE)																		
26	PERSONAL CARE (STRANGER)																		

able and leaving. There are 75 most valuable members (72.82%) and 28 leaving customers (27.18%). The household category is dominated by most valuable members. The mean recency is 181.89 days ago. The mean frequency is 9.07 times within four years. The mean monetary is 10.75 items within four years per member.

Meat

The RFM data showed that the category has 2 (two) customer classes as follows: most valuable and leaving. There are 6 most valuable members (75%) and 2 leaving customers (25%). The meat category is dominated by most valuable members. The mean recency is 170.70 days ago. The mean frequency is 4.75 times within four years. The mean monetary is 5.5 items within four years per member.

Personal Care

The RFM data showed that the category has 2 (two) customer classes as follows: most valuable and stranger. There are 64 most valuable members (62%) and 39 stranger customers (38%). The personal care category is dominated by most valuable members. The mean recency is 151.46 days ago. The mean frequency is 10.63 times within four years. The mean monetary is 13.34 items within four years per member.

Peak Hour based on Customer Profile

The table below shows the buying patterns of the most valuable customers. The peak hour is at 9 am for each category except for meat. In the evening, the sales rise again but not as concentrated as the morning. The time span for the evening peak hour is from 21-22. The recommended time to send any kind of notification and message blast is in the morning before the peak hour. For non-busy hour, it is a good time to do flash sale.

Conclusions

1. The customer buying pattern is identified by using RFM and clustering method. The RFM method is able to show the recency, frequency, and monetary value of customers. After the RFM value of each customer is known, customers are clustered into several groups using K-Means. The clustering

Table 6. Marketing Objectives based on the Customer Profile

Product Category	RFM Pattern	Customer Profile	Marketing Objective	Priority Level
C1	R↑F↑M↑	Most Valuable Customer	Increase Word of Mouth, maintain loyalty	2nd
C2	R↑F↑M↓	Barnacle	Increase product type quantity	3rd
C3	R↑F↓M↑	Big Basket Shopper	Increase purchase frequency	2nd
C4	R↑F↓M↓	First Timer	Increase engagement	3rd
C5	R↓F↑M↑	Churn Valuable Customer	Increase engagement, loyalty, and repurchase	1st
C6	R↓F↑M↓	Churn Barnacle	No special treatment	4th
C7	R↓F↓M↑	Churn Big Basket Shopper	Increase engagement, higher purchase frequency	1st
C8	R↓F↓M↓	Stranger	No special treatment	4th

Table 7. Marketing Strategy and Promotional Offers and Messages

Objective Code	Marketing Objective	Marketing Strategy	Promotional Offers and Messages
M1	Increase Word of Mouth	Referral program	Invite friend to register in Bigbasket.com and buy product X. Your friend should enter your invitation code. Only valid if your friend is a new user in bigbasket.com
M2	Maintain loyalty and ensure repurchase	Subscription program	Be a Bigbasket subscriber today! Subscribe product X daily, weekly, or monthly with payment in due time. Free/discount for delivery service.
M3	Increase engagement	Discount	Big offer! xx% discount for product X. Only available this week. Buy now before it's too late!
M4	Increase purchase frequency	Coupon program	Get coupon for product X. Gather 5 coupon to rebate free product X or Y.
M5	Increase product type quantity	Bundling program	Buy product X will get you free/discount of product Y. Best value only for you.
M6	No special treatment	Do nothing	

method forms different clusters with different RFM values and characteristics. The customers in the same cluster are likely to have similar buying behaviors.

2. The customer clusters can be formed and profiled differently based on every product category. Each customer can be classified as a different profile depending on the product category.
3. The best time to deliver notifications and personal messages is near or at the beginning of the peak hour.
4. The offering content of contextual marketing and targeted advertising can be designed by adapting to the customer profile and the timing of message delivery based on the peak hour of customer buying time.

Managerial Implication

The implication of this research is that the grocery e-commerce can design the most suitable contextual marketing and targeted advertising based on customer profile matrix and the hourly purchase behavior. Therefore, the company can deliver efficient marketing promotions or offers that are relevant to each customer at the best timing based on their changing buying pattern.

Contextual Marketing Design

Set Marketing Objectives

Based on the RFM customer profile obtained, customers can be classified as different clusters depending on the product category. By knowing the customer clusters, we could set the marketing plan differently and reduce the unnecessary marketing cost.

Giving offers to churn valuable customer and churn big basket shopper are the highest priority. Secondary priority goes to most valuable customer and big basket shopper. Third priority goes to the first timer and barnacle customer. And the last are churn barnacle and stranger customers that need no special treatment.

Select Targeted Promotional Offers

Map the marketing objectives into a marketing strategy and the template of promotional offers and messages. For the Bigbasket case, it can be defined as follows.

Select Advertising Channel

The first channel is the banner in every product category. The second one is direct mail marketing. And thirdly is SMS.

Timing of Ads Delivery

As shown in Table. 5, the peak hour in general is around 9 am in the morning and 8 pm at night. Some of the categories also have peak hours outside those hours. If Bigbasket would like to send notifications and message blast, it is recommended to send them in the morning and evening before the peak hour.

Targeted Advertising

Now that we already have the contextual marketing design, the next step is to put it into action in targeted advertising logic that can be implemented using information technology. The most important thing is the logic or algorithm of the targeted ads. So, whenever a customer visit Bigbasket.com or BigBasket app, the system should get the ID of the visitor, which could be based on the IP address (if the user does not log in) or the user ID (if the user logs in). The system then read the member ID. If the system already receives the member ID then the information regarding customer cluster could also be obtained from the customer cluster database.

Targeted Direct Mail

Direct mail is sent to each customer differently depending on the customer profile.

Targeted App and SMS Notification

SMS should only contain one or two offers based on the highest priority message. The timing to send SMS is at the beginning point of peak purchase. For example, if a member's peak purchase is between 10 to 12, then the notification should be sent at 10 am.

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