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Examining E-commerce's Potential for Big Data-Driven Targeted Marketing

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Abstract- The topic of how to build and assess marketing for electronic commerce that is based on big data was discussed. In order to facilitate this expansion, cutting-edge technology was used to the process of developing the individual components of an intelligent precision marketing framework's linked system. We also went through the procedures for running the business and the organizational structure. In order to fulfill the "precision" division that was requested by the customer, an RFMA model was developed in conjunction with the features of the power supplier. This helped to compensate for the disparities between e-commerce and conventional retail. This was done in order to appease the "precision" department of the customer. Finally, it is clear from the data on business-to-consumer transactions that were utilized in the validation of the marketing model that this model was able to provide appropriate marketing strategies that addressed the challenges brought on by big data.

keywords- Big data, online commerce, and precision marketing.

1. INTRODUCTION

According to the findings of a study conducted by McKinsey on data from western industrial sectors, effective usage of big data might increase profit margins for the majority of companies by as much as sixty percent (Bughin, Chui, & Manyika, 2010). The true value of big data is seen in the enormous economic possibilities it has. The business community is now concentrating its efforts on figuring out how to utilize this data to guide management choices. It has become one of the most significant strategic objectives for energy suppliers to be able to accurately integrate and analyze the data pertaining to the behavior of their customers, and then to make use of the findings in order to increase the efficiency with which their company markets its products and services. Although there are some studies that make use of intelligent technology in marketing, the majority of these studies concentrate on

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the efficiency of various marketing applications. However, in order to make effective use of intelligence technology in the process of marketing decision making, the great majority of studies lack comprehensive application analyses and practical research and instead have a broad theoretical character. As a consequence of this, the applications of intelligence technology that now get the greatest attention include customer relationship management, market segmentation, and dynamic pricing, amongst other things. On the basis of an advanced intelligent network, Xu weiting and his colleagues developed a theoretical framework for "smart marketing" (Ping, Shenzhen, and Yang, Xie, 2013). This framework was constructed. This framework provided a full explanation of the alterations that were made to the fundamental concepts and principles of intelligent marketing. An approach to intelligent cross-platform marketing that is based on open-end funds was developed by Chen Xin and his colleagues (Hughes, MA, 1996). The name given to this vehicle was F * OPIM. This tactic makes an effort to bridge the gap between the provision of advisory services, fund advertising, and post-purchase assistance.

Develop an intelligent precision marketing system by fusing together crucial clustering algorithms, intelligence technologies, and power supply features. It is necessary to include this process into a framework. Empirical study has shown that customer segmentation based on RFMA is more accurate and assists businesses in locating potential new customers within their current audience. Because of this, there is a decreased risk of making mistakes that are connected to marketing choices.

2. The Development Path Of E-Commerce Marketing In The BigData Condition

Since the advent of online shopping, an increase in the number of people using the internet, and the proliferation of different types of network terminals, the volume, complexity, and pace at which data is created have all substantially increased. Intelligence has emerged as the single most essential value carrier for the further development of e-commerce marketing as a result of the growth in both the volume of data and the expectations of consumers. The use of intelligence technology has been shown in a number of studies to be capable of processing enormous volumes of data, which can then be evaluated to provide pertinent information and assist in decision-making. In the last ten years, data mining has seen substantial growth, yielding remarkable achievements in the fields of marketing, sales, human resources, e-commerce, and other commercial domains (Yan, Pingzhi, Xun, Guo, and Zeng, China, 2013). As a direct consequence of this, it is reasonable to assume that the growth of marketing via e-commerce will occur in a manner that is prompt, precise, and consistent. Responding swiftly is the only way to properly review data while leveraging cutting-edge technology and make rapid, dynamic alterations to marketing strategies. Because of the internet and large amounts of data, the behavior of consumers is continuously shifting and is becoming more dynamic. As a direct consequence of this, businesses are required to act rapidly in order to adapt their marketing strategy to the new changes. The ability to access genuine customer behaviors, thoughts, and reactions to content, in addition to maintaining an accurate record of consumer information, makes big data a very important resource. Big data now has a big competitive edge. The capacity to precisely identify customer groupings, information interaction points, and marketing operations is one definition of precision. The capacity to perform each of these functions accurately is what we mean by accuracy. Shorter information cycles, brought about by shifts in the dynamic behavior of customers and consumers, directly lead to increased levels of stability. The usage of data is an ongoing need for companies in order to solve problems brought about by insufficiently investigated information.

3. The Frame work Of Intelligent Precision Marketing Based On The R fma

The first thing that needs to be done in order to achieve intelligent precision marketing is to analyze the behavior of customers using the many tools that are presently accessible for gathering information. After that, distinct client groups are categorized and separated from one another in order to make marketing decisions that are tailored exclusively for that customer groups. Last but not least, it has been shown that the integration of objective data with active input (in this case, comments from customers) has positive results. This lays the path for more advances to be made in the degree of targeted marketing and its effectiveness.

You may construct several types of customers by using the K-means clustering technique and the updated RFM model, both of which are based on an analysis of data relating to consumer behavior. Lastly, you need to devise a plan that is tailored to each individual sort of consumer. The hierarchy of the three different framework levels is shown in Figure 1 from highest to lowest. The data layer, the analysis layer, and the decision-making layer are the three layers that make up this structure. There are three layers of interrelated components that work together to make precise marketing to e-commerce providers possible.

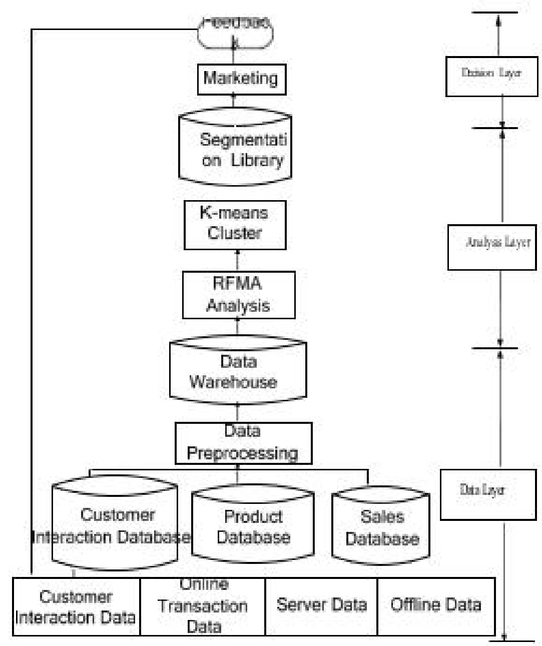

Figure1.Framework of intelligent precision marketing based RFMA model

- **Data Layer**

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Data layer is responsible for receiving real-time data, combined with basic customer information, business information and consumer attributes and other data which is obtained from various sources, and preprocess these data, load the data warehouse for the next phase of data mining and intelligent analysis to prepare.

- **DeterminingDataSource**

According to Wan, Hong, and Wan, Yan (2010), some of the data sources for this model include server data, data pertaining to online transactions, data pertaining to client interactions, data pertaining to offline activities, and other pertinent data. Transaction data from online businesses often include details about the e-commerce website itself, as well as details about users, purchases, and other information that is kept in a conventional relational database. There are two different kinds of server data: web logs and proxy server-side data. For instance, pricing of commodities, sales, item qualities, and so on are all examples. Customer registration and feedback are examples of the types of information that are included in data pertaining to customer interactions. Customers use the website to input and submit pertinent information that will be used for client registration, and the server is the one that gets this information. Personal information about the consumer, information about the products purchased, difficulties and requests expressed by the customer, and so on are all collected. The term "feedback information" is often used to refer to data that has been sought for and acquired online, in addition to assessment data that has been bought. The term "offline data" refers to inventory,cost,and logistics information in e-commerce enterprises.(Wang,Feifei,&Li, Jing,2012)

- **Data Preprocessing**

According to the theory of big data (Ying Ho, Yuho Chung, and Kinnam Lau, 2010, June), the data generated by e-commerce businesses is both extensive and highly dimensional. It is necessary to prepare the data since the raw data obtained from any data source is likely to have errors, such as missing numbers, duplicates, or incomplete data, among other types of errors. It is necessary to lessen the dimensionality of the data in order to increase its quality and match the requirements of the application (Ping, Shenzhen, and Yang, Xie, 2013). This may be accomplished by cleaning and switching the data. The organization of the user's recorded data, construction of the data set necessary for the next phase, and loading of the data warehouse are the primary responsibilities of the data preparation stage.

➢ **AnalysisLayer**

Utilizing intelligence technology and associated algorithms, the analysis layer's primary duty is to examine, evaluate, and get access to data that can be put to productive use in order to provide assistance with marketing decision-making. This layer acts as the cornerstone of the marketing framework by doing an analysis on a huge quantity of data pertaining to customer behavior. The RFMA model and K-means clustering are used in order to discover various market groups and consumer types. This tier is responsible for providing the marketing choice for the level that comes after it.

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- **The Background of RFM Model**

The RFM concept does not infringe on the privacy of individuals, and it is quite easy to have access to information on purchases. It is well suited for conventional retail sectors that provide customers a wide variety of items, commodities that are often available at reasonable prices, and things that are frequently bought. The fundamental concept is to determine the worth of the client by analyzing the client's behavior in accordance with the following three major behavioral characteristics (Hughes, MA., 1996): R is the amount of time that has passed from a customer's most recent purchase and the present; according to Wu, C. and Chen, H.L. (2000), a lower R indicates a higher level of customer value.; The greater the customer's buy frequency, the greater the customer value (Lemon, K.N., White, T.B., & Winer, R.S., 2002). Likewise, the greater the customer's quantity of consumption over time, the greater the customer value (Lemon, K.N., White, T.B., & Winer, R.S., 2002).

- **The Improved Basis of RFM Model**

However, there are very few concrete manifestations of the notion, and marketing strategies are still in their formative stages (Rule and Attaining, Wang and Jiaqiang, Tu and Huan, et al., 2012). According to research conducted by academics from other countries (Maia, M., and Almeida, J., 2008), the method of consumer segmentation has a direct bearing on the precision of data mining technologies. great consumption does not always translate into great customer value over the course of time. It is possible that increased spending will lead to an increase in a company's profits; nevertheless, this is not a sufficient explanation for customer pleasure or long-term consumption trends. That does not adequately represent the true worth of a customer. For instance, some clients could have lower consumption rates and make less purchases, but their evaluations might be higher than average, which would make them prospective consumers for businesses. As a consequence of this, the clustering feature of the RFM model could provide inaccurate conclusions.

When connected with the actual e-commerce environment, businesses that engage in e-commerce have comprehensive records of the activity of their customers, which makes it simpler to get such information. As a direct consequence of this, the new approach positions assessment as the primary basis for segmentation. Because it comes directly from the customers, feedback from them is a crucial signal.

- **Clustering**

Clustering is a method that is often used to categorize many sorts of research, including market and customer groupings. People who had significant differences were divided into groups, which might eventually lead to people within the same class having a higher degree of similarity (Liu, Heroic, and Bong, 2006). The clustering of information based on sales data and consumer purchase information is useful for determining the various types of consumers and generating effective marketing strategies. K-means clustering is put to use in this study to discriminate between the various consumer types and ensure the successful implementation of the subsequent stage in the process of precision marketing choices.

- **Decision-MakingLayer**

The RFMA model classified customers into three distinct groups: loyal long-term customers, prospective new customers, and customers who were on the verge of canceling their service. Take suitable actions and formulate marketing strategies in accordance with the various types of customers you serve. Following the

- **Data Standardization**

in order to prevent making mistakes that are more significant due to the outcomes of clustering a lot of different units of measurement. As a consequence of this, we need to normalize every kind of data. For the purpose of providing normalized data for each of the indices ZR, ZF, ZM, and ZA, this study used a method known as poor standardization. By normalizing each number to fall inside the range [0, 1], we were able to lessen the dimensional impact. The formula may be written as follows: i stands for the ith client, and j stands for each client that is held by R, F, M, and A respectively.

$$X_{ij}' = \frac{X_{ij} - \min\{X_{ij}\}}{\max\{X_{ij}\} - \min\{X_{ij}\}}$$

- **Clustering Results of RFMA Model**

execution of a marketing plan tailored to each kind of consumer, the next step is to actively engage with those customers by gathering information about their prior interactions with the product or service as well as any suggestions they may have. Within the context of the marketing framework, feedback data are continually updated, discussed, and leveraged to promote product or service innovation. The 4C concept and its customer-centered attitude are both congruent with the fact that
the customer experience has always been a major component in the creation and execution of marketing plans.

Taking the scale and the number of customers into account, take the value of K is 3, avoiding the results of classification are too detailed, the understanding deviation are too large to each groups. Clustering results are shown in Table 1 as below:

Table 1. Final cluster centers of RFMA model

Clustering Properties	1	2	3
ZR	0.2242	0.0439	0.4856
ZF	0.2415	0.5594	0.5130
ZM	0.1546	0.5148	0.3788
ZA	0.7000	0.7230	0.1330

Table2.The number of customers per cluster in RFMA model

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Cluster	1	16.000
	2	13.000
	3	21.000
Valid		50.000
Missing		0.000

According to the findings of the RFMA model, each of the three groups of consumers has a respective total of 16, 13, and 21. The first class of customers, who have the lowest levels of consumption and frequency, as well as the shortest time since their last purchase, are potential customers in businesses that receive the appropriate marketing to pique their interest. The second class of customers, who are the company's loyal customers, have the highest ratings, the highest levels of consumption, the highest frequency of purchases, and the longest time since their last purchase. This class of customers also has the longest time since their last purchase. Loyal customers make a contribution to the company at a rate that is proportionate to their share of the profits generated by sales. The 80/20 rule, according to the Pareto chart.

- **RFM Model Clustering Results**

Also taking the sample data K = 3 based on the RFM model, clustering results as shown in Tables 3 and 4

Table 3. Final cluster centers of RFM model

Clustering Properties	1	2	3
ZR	0.1150	0.1627	0.6718
ZF	0.2775	0.6203	0.4351
ZM	0.2202	0.5190	0.2940

Table4.The number of customer sper-cluster in RFM model

Cluster	1	19.000
	2	14.000
	3	17.000
Valid	50.000	
Missing	0.000	

The findings of the clustering performed by the RFM model indicate that each of the three categories has 19, 14, and 17 consumers respectively. The second class of customers is the company's most loyal customers because they make the most purchases, do so most frequently, and do so with the shortest interval between purchases. The first class of customers is the company's least loyal customers because they make the fewest purchases, do so less frequently, and their interval between purchases is the shortest. The third class of customers is the company's most loyal customers because they make the most purchases, do so more frequently, and their interval between purchases is the longest.

4. CONCLUSIONS

When the model was improved, there were less prospective consumers and devoted customers, but there were more customers who had stopped purchasing altogether. This is in contrast to the findings of the two clustering methods. This is due to the fact that if the customer evaluation is ignored, it is more likely that customers will be categorized as transient clients in the future. This will rely on the amount that they consume, the frequency with which they make purchases, and how recently they have made purchases. Should the evaluation be taken into account, on the other hand, customers who have received good ratings in this particular area will be categorized as potential consumers. If evaluation is not carried out, it is possible that existing customers, such as the one in the previous example, would be categorized as potential consumers in the future. However, in light of the feedback from previous customers, these individuals constitute a possible loss of business. Therefore, the classification of e-commerce is more "accurate" after the inclusion of customer evaluation; it can help businesses in identifying potential customers who are spending less money, purchasing less frequently, but giving a high evaluation; these customers are likely to be from the "petty bourgeoisie" class or students; this group seeks "affordable" in reality, because their income is limited, so the amount of consumption and the purchase frequency are relatively low; however, they give a high evaluation. However, since they are more satisfied with the goods or services that the company provides, e-commerce sellers can lower the price of the commodity or service in order to make it seem to be more expensive in their eyes, which would result in them being loyal consumers of the business.

Clustering analysis based on RFMA may be of use to businesses in identifying customer groups who have higher consumption rates, higher frequency within a given time, longer intervals between recent purchases, lower evaluation ratings, and less need for continued relationship management. This demographic has a high income, has a strong interest in style and brands, and does part of their shopping online, which is reflective of real-world behavior. Customers that get an unacceptable score may be eliminated completely in an attempt to save costs associated with the marketing activities of the company. This marketing strategy is analogous to the BCG matrix for the "skinny dog" market approach, and it entails focusing on niche markets.

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