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AHP Based Data Mining for Customer Segmentation Based on Customer Lifetime Value

Manidatta Ray[1],B. K. Mangaraj[2]
[1]Asst. Professor (Decision Science and Operations Management Area), Birla Institute of Management Technology (BIMTECH), Bhubaneswar, India
[2]Professor (Production, Operations and Decision Sciences Area), XLRI, Jamshedpur, India
E-Mail: manidatta.ray@gmail.com, manidatta.ray@bimtech.ac.in

Abstract- Data mining techniques are widely used in various areas of marketing management for extracting useful information. Particularly in a business-to-customer (B2C) setting, it plays an important role in customer segmentation. A retailer not only tries to improve its relationship with its customers, but also enhances its business in a manufacturer-retailer-consumer chain with respect to this information. Although there are various approaches for customer segmentation, we have used an analytic hierarchical process based data mining technique in this regard. Customers are segmented into six clusters based on Davis-Bouldin (DB) index and K-Means algorithm. Customer lifetime value (CLV) along four dimensions, viz., Length (L), Recency (R), Frequency (F) and Monetary value (M) are considered for these clusters. Then, we apply Saaty’s analytical hierarchical process (AHP) to determine the weights of these criteria, which in turn, helps in computing the CLV value for each of the clusters and their individual rankings. This information is quite important for a retailer to design promotional strategies for improving relationship between the retailer and its customers. To demonstrate the effectiveness of this methodology, we have implemented the model, taking a real life data-base of customers of an organization in the context of an Indian retail industry.

Keywords: B2C marketing, Clustering, Customer life- time value; Value-based segmentation

I. INTRODUCTION

The field of data mining (DM) has its origins in statistics and machine learning. It involves an iterative process within which progress is defined by discovery, either through automatic or manual methods. It is the process of extracting valuable information and knowledge from huge amounts of data (Hanand Kamber, 2006) that uses various techniques, viz., computing, mathematical, optimization, and statistical to extract and identify hidden patterns and subsequently gain knowledge from large databases. For example, from a customer data-base, the technology involved in data mining can provide business intelligence to generate new opportunities and hence, is most useful in an exploratory analysis scenario where there are no predetermined notions about what will constitute an ‘‘interesting’’ outcome. A major benefit of using a data mining technique is that, it bypasses the knowledge acquisition bottleneck by unearthing the patterns or knowledge from the data itself. However, these methods obviate the need for eliciting knowledge from human experts. The major task of data mining can be classified into two categories, viz., descriptive and predictive. Clustering is an instance of descriptive methods, whereas classification is an example of predictive methods (Han and Kamber, 2006).

The techniques of data mining help to accomplish its goal by extracting or detecting hidden customer characteristics and behaviours from large databases. However, the main feature of it is to build a model from data where the technique can also perform one or more of the following types of data modelling: (1) Association; (2) Classification; (3) Clustering; (4) Forecasting; (5) Regression; (6) Sequence discovery; (7) Visualization etc.. Some of the widely used data mining algorithms involve: (1) Association rules; (2) Data envelopment analysis; (3) Decision trees; (4) Genetic algorithms; (5) Neural networks; and (6) Linear/logistic regression analyses. Association rules try to establish relationships that exist between data-items in a given record. Apriori algorithms and statistical methods are commonly used tools for association modelling. Classification is one of the most common learning models and some of the frequently used techniques for this are neural networks, decision-trees and if-then-else rules. Clustering is the process of segmenting a heterogeneous population into a number of homogenous clusters where neural networks and discrimination analyses are used to determine these clusters. From a record’s pattern, forecasting estimates the future value of an outcome based on commonly used tools that include neural networks, survival analyses, regression analyses etc. Linear regression and logistic regression are some of the popularly used tools for forecasting. Sequence discovery is the process of identification of associations or patterns over time and tools, such as, set theory and statistical methods are used for the purpose. Visualization refers to the presentation of data so that users can view complex patterns. This is also used in conjunction with other data mining models to provide a clearer understanding of discovered patterns. Examples of visualization model are 3D graphs, ‘‘Hygraphs” and ‘‘SeeNet”.

.Various techniques of data mining are used in different areas of marketing management, such as, customer relationship management (CRM) (Ngai et al., 2009), market basket analysis (Berry and Linoff, 2004), customer churn prediction (Coussement and Van den Poel, 2008) etc. Customer segmentation is also another important application area of data mining, particularly for clustering in CRM. It involves partitioning the customer-base into a number of smaller homogeneous customer segments according to their similarity based on several techniques as discussed. From the literature, it can be seen that, most of the researches in the CRM area belong to the B2B (business-to-Business) setting. However, in this study, we have considered a B2C (Business-to-Customer) set-up and addressed the issue taking a real life case of a manufacturer-retailer-consumer chain (MRCC). This is because, the role of retailers is crucial in persuading consumers to purchase products of a typical manufacturer in such a chain. As product homogeneity for any product increases the number of choices for consumers, it complicates the decision-making process and in such a situation, any recommendation from the retailer regarding a particular brand or product influences customers' purchase decisions. As a result, by improving its relationship with customers, a retailer can gain greater benefits and in this regard, customer segmentation enables retailers to better understand them in order to adopt right and segment-specific marketing strategies for them. Consequently, execution of such a segment-specific marketing program leads to a profitable as well as long-term relationship between retailer and its customers.

In this study, we propose a methodology for value-based customer segmentation using a data mining technique involving analytic hierarchical process (AHP), as suggested by Saaty (1980). Four dimensions of customer life- time value (CLV) are considered as the criteria to determine the weights of these segments. In section 2, we discuss the relevance of B2C marketing in the context of a retailing environment and the concept of CLV for customer segmentation in terms of four dimensions, viz., viz., Length (L), Recency (R), Frequency (F) and Monetary value (M). We also highlight the necessity of identifying optimum clusters and associating weighted LRFM values to each of the clusters for their differentiation. Section 3 discusses the AHP based methodology for the study in detail. In section 4, an empirical study, taking a real life data of a firm in the context of an Indian retail industry, is presented considered for the implementation. Section 5 concludes the study stating the scope for further research in this direction.

II. BACKGROUND

2.1 Business-to-Customer market segmentation

Business-to-Business (B2B) organizations don’t sell their products or services to end customers directly and they do that via intermediaries. For example, the manufacturer of a typical product distributes its products to some retailers, and then they sell those items to the end-customers. However, the success of a B2B organization depends on its intermediaries. For instance, in a MRCC, the manufacturer needs to rely on the co-operations from the retailers in order to sell a large volume of products to make profit. Therefore, identifying the high value and profitable retailers is an essential task for the manufacturer, and in this regard, segmentation tools help in identifying different groups of retailers. Some studies have been made in this area, which focused on customer loyalty. For instance, Lam et al. (2004) proposed and analyzed a conceptual framework for identifying factors affecting customer loyalty in a B2B context, including customer perceived value, customer satisfaction, and switching costs. Davis-Sramek et al. (2009) also investigated factors influencing retailer’s loyalty in the supply chain for consumer durable productsHowever, in the era of modern retailing, business-to-customer (B2C) approach is very much important due to varied type of customers in the Indian marketing environment. Hence, in this context, customer segmentation for a retailer plays an important role in designing various customer-specific marketing strategies. There are numerous approaches in this regard and are divided into customer need-based, characteristics-based (Greengrove, 2002) and value-based segmentation (Kim et al., 2006). In the literature, several data mining techniques have used these concepts to group customers in different businesses and industries, such as hardware retailing (Liu and Shih, 2005), retail industry (Ho Ha, 2007), textile manufacturing (Li et al., 2011), electric utility (Lopez et al., 2011) and so on. In the present study, we have used value-based segmentation in a MRCC to identify different groups of customers according to their differential values. Customer segmentation based on customer value is an approach that identifies profitable customers and to develop strategies to target them. Customer value is often known as LTV (Life Time Value), CLV (Customer Lifetime Value), CE (Customer Equity) and customer profitability (Kim et al., 2006). According to Kottler (1974), CLV is “the present value of the future profit stream expected over a given time horizon of transacting with the customer”. Various models are developed in the literature for measuring CLV (Gupta et al., 2006), among which, the RFM (Recency, Frequency and Monetary) model developed by Hughes (1994) is an important one. Chang and Tasy (2004) extended the RFM model by adding another dimension, i.e., the customer relation length (L) to it, thereby developed the LRFM model.

III. WEIGHTED LRFM

The RFM model has three dimensions: (1) Recency: is the time interval between the last purchase and a present time reference; the shorter the time interval, the bigger R is; (2) Frequency: is the number of customer’s purchases in a particular period; a higher frequency is more valuable and (3) Monetary value: the total amount of money consumed by the customer over a particular time period; the higher the monetary value, the bigger is the contribution to business. Although RFM and its successor LRFM made it possible to assess CLV, there are also some challenges to use them in an effective manner. The major challenge relates to the importance of four variables, viz., L, R, F, and M, followed by the determination of their corresponding importance in the assessment environment. Experts have differing views on this issue. For instance, regarding the RFM model, Hughes (1994) showed that the importance (weight) of the three variables is equal, while Stone (1995) considered different weights for the RFM variables. However, the weight of each RFM variable depends on the characteristics of the industry. Some researchers have already used the weighted RFM model (e.g. Liu and Shih, 2005; Seyed Hosseini et al., 2010) in their studies. It is important to note that, in the studies that used weights in the RFM and LRFM models (e.g. Liu and Shih, 2005; Seyed Hosseini et al., 2010), no relationship was found between the variables. As a result, the LRFM variables were considered as independent. For example, the high frequency does not affect the high monetary value and vice versa. In this context, we determine the weights (relative importance) of each LRFM variable based on the inputs of a survey.

IV. CLUSTERING

Clustering, which is a subset of unsupervised learning techniques, is the process of grouping a set of objects into

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classes of similar objects. There are many clustering methods, including partitioning methods, hierarchical methods, density-based methods, grid-based methods, and model based methods (Han and Kamber, 2006). K-means clustering forms the category of partitioning methods and is the most widely used clustering algorithm in CRM and marketing. In this regard, this algorithm introduced by MacQueen (1967) can process large amounts of data quickly. The operation of K-means clustering is as follows: (1) selecting K initial centroids; (2) assigning each object to its closest centroid; (3) updating the centroid of each cluster to the mean of its constituent instances; and (5) repeating steps 2 and 3 until centroids stop changing.

Table 1: Numbers representing paired comparison judgments

Comparison Importance	Description
1	Equal
2	Intermediate between equal and moderately dominant
3	Moderately dominant
4	Intermediate between moderately and strongly dominant
5	Strongly dominant
6	Intermediate between strongly and very strongly dominant
7	Very Strongly dominant
8	Intermediate between very strongly and extremely dominant
9	Extremely dominant

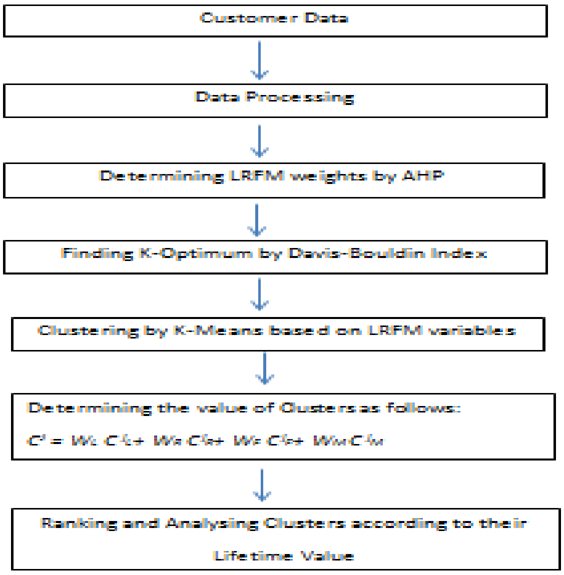

Fig. 1: The Proposed Methodology

Analytical Hierarchy process (AHP): The Analytic Hierarchy Process (AHP) developed by Saaty (1980) is a method for multi-criteria decision-making. It is useful for assessing multiple alternatives with respect to multiple numbers of criteria based on human assessment. It uses paired comparison judgments from a fundamental scale of absolute numbers approached by decision-makers to prioritize alternatives for a problem in an architectural structure (Saaty, 2003). Decision-makers assign a number for each pairwise comparison in a 1 to 9 to point scale (Table 1). This method also measures the degree of inconsistency between judgments. If the degree of inconsistency exceeds 0.1, then the judgments must be revised. Methodology Our proposed methodology for customer segmentation is shown diagrammatically in Figure 1. Here, we use the LRFM model in determining the value of each customer.

V. THE EMPIRICAL STUDY

5.1 Customer Data

The case study in this research is a large super- market store in Indian context, having different sections, such as apparel, men, ladies, kids, personal grooming, toys and gifts, home shops, and shoes and accessories. Each of these sections has a wide range of products. This retail firm has three stores in Odisha and currently is also expanding to Bengaluru as a first step to become national retailer. The management of this store is interested to rank customer groups based on their values, so that appropriate marketing strategies can be developed for them. For improving retailer-customer relationship, this requires customer segmentation as a first step that has an important role in determining these strategies.

5.2 Data Processing

Data Processing is an important step in data mining methodology, as it improves the accuracy and efficiency of subsequent modelling (Han and Kamber, 2006; Tan et al., 2005). In this paper, data processing techniques such as, data-cleaning, data- transformation, data- integration and data-reduction are used to improve the quality of data for clustering. Customers who didn't make any purchase during last one year are removed from the data-set. After performing this step, we reach to a data- set with 1600 customers. From the integrated data-set, the L, R, F and M variables are extracted for each customer. In this case, the

L value (customer relationship length) is computed six-monthly; because of large value of L has negative effect on clustering.

5.4 Determining LRFM weights by the AHP

In this paper, the AHP method of Saaty (1980) is used for calculating the LRFM weights according to the opinion of decision makers. This is done through a 3- step process, according to the AHP explanation. First, four decision makers from the three different management layers of the sales department are selected for making paired comparisons. In the second step, the inconsistency index is computed and checked for each decision-maker's judgement. Finally, LRFM weights are determined by computing eigen values of the judgement matrix and found to be 0.238, 0.088, 0.326 and 0.348 respectively.

5.3 Finding the K-optimum by the Davies-Bouldin index

Many clustering algorithms have been introduced in the past; however, there is no best algorithm in this regard. In fact, due to the exploratory nature of clustering, seeking the best clustering algorithm is meaningless. Yet, the K-means algorithm is the most popular partitioning algorithm (Jain, 2010) as can be seen in the literature. According to Jain (2010), despite of being proposed over 50 years ago, K-means is still one of the most widely used clustering algorithms.

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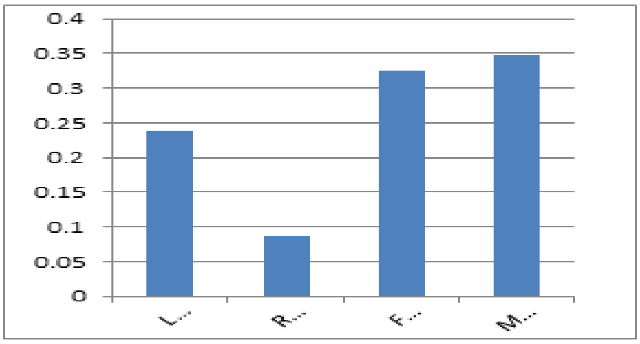

Fig.2. LRFM weights obtained from AHP

The main reasons for the popularity of K-means are its easy implementation, simplicity, efficiency, and practical success.In this study, we use the K-means algorithm for clustering customers and require determining the number of clusters. As the improper selection of k as the number of clusters may lead to inaccurate results, there are useful clustering quality indexes that can help in determining the optimal number of clusters. In this study, we use the Davis-Bouldin index (Davis and Bouldin, 1979) for this purpose, where the aim of this index is to identify the sets of clusters that have small intra-cluster distances and large inter-cluster distances. This index is defined as:

$$DB = \frac{1}{k}\sum_{i=1}^{k} \max_{i \neq j}\left\{\frac{a_i + a_j}{d(C_i, C_j)}\right\} \qquad (1)$$

where, k is the number of clusters; ai is the intra-cluster distance of cluster i ; and d(Ci , Cj) represents the inter-cluster distance between clusters i and j . The number of clusters that minimizes the DB index is taken as the optimal number of clusters.

5.5 Clustering by K-Means based on the LRFM variables

In this stage, customers are segmented into the number of clusters, as identified in the previous step, using k-means and LRFM variables. In this case, the number of clusters for the k-means algorithm is set to be 6. Hence, after performing the clustering algorithm, we obtain the clusters as shown in the table- 2.

Cluster	# Customers	Length	Recency	Frequency	Monetary
1	151	506.83	201.19	15.28	360301.49
2	350	512.2	197.14	14.55	234518.51
3	135	504.04	215.15	14.6	41914.52
4	307	517.8	194.41	15.09	96540.38
5	305	520.86	205.48	15.3	305767.37
6	352	522.49	197.37	16.34	163056.85

Table-2 Clustering Results

5.6 Calculating the values of Clusters

To calculate the value of each customer segment, we normalise the LRFM variables for centroids by using the Min-Max normalization method which has been discussed by Han and Kamber (2006). Having normalised the LRFM values, we calculate the CLV of each cluster as follows:

CJ = WL C jL+ WR C jR+ WF C jF+ WM C jM (2)

Where Cj : LRFM rating for cluster j,
C jL, C jR, C jF, C jM: normalised values of L, R, F and M for cluster j, and
WL, WR, WF, WM : weights of L, R, F and M obtained from AHP.

Table 3: Clusters information

Cluster	# Customers	Length	Recency	Frequency	Monetary	CLV	CLV Rating
1	151	120.6266	17.70432	4.980675	125384.9	125528.2	1
2	350	121.9043	17.34857	4.743766	81612.44	81756.44	3
3	135	119.9608	18.93304	4.7596	14586.25	14729.91	6
4	307	123.2367	17.10812	4.920795	33596.05	33741.32	5
5	305	123.9652	18.08241	4.986197	106407	106554.1	2
6	352	124.3516	17.36875	5.328063	56743.79	56890.83	4

4.7 Ranking and analysing the clusters according to lifetime values

After calculating the CLV for each cluster, we rank the clusters according to their CLV values which can help the managers to allocate marketing resources according to the profitability of each segment. In addition, an in-depth analysis of each segment with respect to LRFM also informs the firm about the purchasing behavior of customers in each segment. This enables marketing managers to develop effective marketing strategies that can lead to a profitable long-term relationship with the customers. In order to analyze the clustering results, we employ the customer value and customer loyalty matrices for the purpose. The customer-value matrix proposed by Marcus (1998) uses two parameters, viz., the customer buying frequency (F) and the monetary value (M) as its two axes.

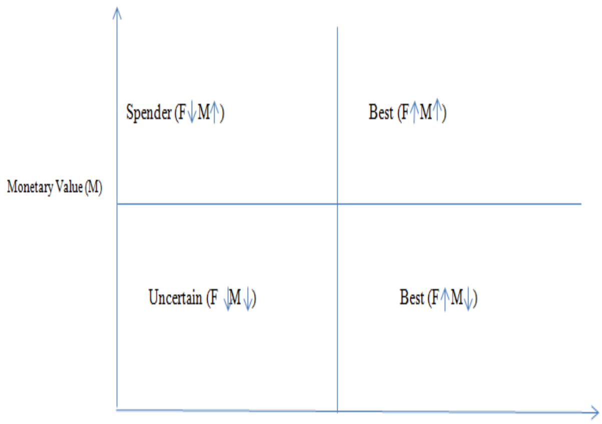

Fig. 3: Buying Frequency (F)

Two other indicators, such as, customer relationship length (L) and recency (R) relate to customer loyalty, and we can also consider them in the customer loyalty matrix. According to the

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pooled opinion of some marketing experts, new customers are those who have launched their relationship with the firm in the last 1.5 years (three six month periods). Based on this assumption, we consider the customers with their L (length of relationship) lower than 3 as the new customers, and those with their L higher than 3 as the long life (established) customers. For the recency indicator, the two states, viz., Low and High are taken. If the recent transaction time of a cluster is smaller than the average total value, it is considered a High Recency value cluster; otherwise, it is regarded as Low Recency. Similarly, Frequency (F) and monetary (M) dimensions have the same states: Low and High. If the frequency/or monetary value of a cluster is smaller than the median point, it is termed as a Low frequency/or monetary value cluster; otherwise, it is a High frequency/or monetary value cluster. After analyzing each segment, we label each cluster according to its status in these variables. Furthermore, we also suggest some possible actions that can be taken, in order to improve the relationship between the firm and customers.

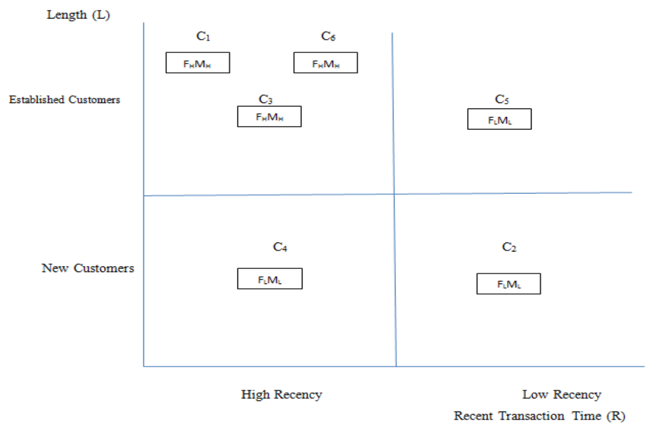

Fig.4 : Clusters Status

Table-4 : Cluster Labeling

Cluster	Cluster Label	Description	Possible actions / Cluster specific Strategies
C1	Platinum Segment	The highest value, the moderate frequency, the moderate recency, and the highest lifetime.	Special attention should be paid in order to retain customers of this segment
C5	Diamond Segment	The second highest value, second highest frequency, second highest recency, and a high lifetime.	There are many customers belonging to this segment. Strong strategies should be developed in order to maintain relationship between the retailers and Customers of this segment.
C2	Golden Segment	This is an average value segment that has low moderate size.	Marketing programs should be developed in order to increase basket size of this segment of customers.
C6	Silver Segment	This segment has low recency, highest frequency, and lower monetary value.	Although they have a long time relationship with the firm, they exhibited very bad performance. In addition, the recency of this segment is very low; this may be a sign of attrition. Strong anti-attrition programs should be developed for this segment of customers.
C4	New Low Value Customer	This segment has lowest recency; lower frequency this means that they hardly maintain their relationship with the retailers. They have low frequency and low monetary value.	Because the number of customers belonging to this segment is relatively high, marketing programs for this segment should encourage customers to buy more products.

VI. CONCLUSION AND SCOPE FOR FUTURE WORK

Data mining has its importance in the field of business in connection with finding patterns, forecasting, discovery of knowledge etc. It has wide application domain almost in every industry, where the data is generated from a data-base for the utilization of most of its important activities. In the context of marketing management, it also has broad applicability and retailing industry is not an exception. However, as compared to the B2B approach, not many studies have yet been done in the B2C framework. At the same time, the evolution of modern retailing in the marketing environment of an emerging economy like India requires in-depth analysis of customer data-base to generate useful information for the retailers. Looking at this important aspect, the present study is designed to analyze customer data-base using a multi-criteria decision making technique based data mining methodology. Thus, in this study of B2C marketing, we have segmented customers of a retail store based on an AHP based data mining a methodology using the concept of value-based segmentation. The concept of customer life- time value has been used to determine the value of each segment, so that, appropriate marketing strategies can be undertaken to improve retailer-customer relationship. We addressed this problem for a manufacturer-retailer-customer chain, focusing on customers, as customers are the end users of the products. The proposed methodology has been implemented using the data of a retail firm, which has got its national presence in India. The results of this study identified and ranked six groups of customers, according to their CLV values. We also presented an analysis of the customers with respect to a customer-value matrix. Finally, we provided some possible strategies that can be considered in order to improve the relationship between the retailer and its customers. However, this study has a lot of scope for its improvement. For example, fuzzy AHP can be used for generating weights of the CLV criteria instead of AHP, where the judgment matrix represents the aggregation of multiple judgments in terms of triangular membership functions. Similarly, after identification of the clusters, CLV values of the clusters can also be determined by the application of TOPSIS (Technique for Order Preference by Similarity to Ideal Soltions).The authors express their thanks to the anonymous Indian Retail Chain for providing all data which was required for the study. In addition, we would like to thank the reviewers for their valuable comments and suggestions for preparation of the revised manuscript.

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