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Measuring and Predicting Customer Lifetime Value in Customer Loyalty Analysis: A Knowledge Management Perspective (A Case Study on an e-Retailer)

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KEYWORDS

Customer Knowledge Management (CKM),
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Customer Relationship Management (CRM),
Corporate Image,
Neural Networks

ABSTRACT

Modern business organizations have appreciated the significance of having competitive advantage through the delivery of continuous improvement towards the customers, and being knowledge-oriented. Indisputably, Knowledge Management (KM) plays a key role in the success of Customer Relationship Management (CRM). In this regard, Customer Knowledge Management (CKM) is a newly developed concept that deals with knowledge from customers rather than knowledge about customers. However, little research has been done on the application of CKM in e-business. In this paper, after an overview of the literature, an application of CKM in Customer Lifetime Value (CLV) measurement is studied in an e-retailer case where Corporate Image and Reputation are taken into consideration.

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1. Introduction

Contemporary business environment has left the managers with no choice but to keep their businesses highly competitive, flexible, responsive, and innovative to survive. Business organizations are experiencing significant competition resulting from globalization, rapid technological advancements, growing dynamics of business environment, and most importantly, growing expectations of customers.

Conventional marketing was based on having single transactions with the customers and customer acquisition; but, as studies have shown, acquiring new customer is up to five times more costly than retaining the existing ones [1], and that the profits generated by existing customers tend to accelerate over time [2]. Recognizing the vital importance of current customer satisfaction and loyalty as a major contributor to the level of competitiveness; managers shifted their marketing strategy to a customer-centric version. In this regard, relationship marketing was developed which focused on maintaining and improving current customers who are profitable for the organization rather than acquiring new ones.

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In other words, Customer Relationship Management (CRM) is a contemporary management tool that manages the relationship with customers by employing up-to-date Information Technology (IT) such as on-line data analysis, data-mining and database management in order to understand, communicate with, and to attract them. Its objective is to satisfy and retain customers [3]. Most of the systems used in CRM deal with information about the customers rather than information from the customers.

One study found that 89% of companies consider customer information to be extremely important to the success of their business (King in [4]). However, information about the customers is not considered a competitive factor anymore and having knowledge has emerged to be more critical than ordinary information. Knowledge extends beyond information such that it deals with facts and ideas that have been acquired mostly through experience and includes formal and informal learning. In this regard, Knowledge Management (KM) enables the creation, communication, and application of knowledge of all kinds to achieve business goals [5]. Customer Knowledge Management (CKM) is a recently-coined subject that focuses on providing customers with desired (knowledge-accessed) behaviors that allow them to access knowledge from themselves (e.g., knowledge resident in themselves) [6].

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Customer loyalty is more complex than customer retention as it involves resistance to switching to other brands. Therefore, various issues regarding brand management such as corporate reputation and image must be taken into consideration. Realizing the importance of customer loyalty, managers can better classify their customers regarding their value to the company and allocate budgets for marketing programs. In this respect, Customer Lifetime Value (CLV) has been an important factor in identifying customers in relation to their loyalty and value [7].

This paper focuses on providing a brief literature review of CRM, KM and CLV and then provides a model of customer segmentation applying KM tools. Finally, the proposed model is applied in a case study of an online retailer of movies.

2. Literature Review

2.1. Customer Relationship Management

Relationship marketing was developed in contrast to the traditional transactional marketing which focused on short-term transactions with customers based on single-sales wherein little emphasis was devoted to customer service.

Customer Relationship Management (CRM) refers to the technology and systems that help the company serve, satisfy and retain customers. The primary goal of relationship marketing (or relationship management) is to build and maintain a base of committed customers who are profitable for the company. From the early stage of introducing CRM, it has been incorporated by many manufacturing and service organizations. Also different segmentation methods have been developed to segment current customer base or to determine the segment to which a certain customer belongs (e.g. [8]; [9]; [10]; [11]).

The results of a research by Reichheld and Schefter [12] shows that by retaining just 5% more customers, online companies can boost their profits by 25% to 95%. Also, it has been proven that acquiring new customers is five times more costly than retaining existing ones. Moreover, the same research shows that acquiring online customers is nearly 20% to 30% higher than traditional businesses that startup companies may remain unprofitable for at least 2 or 3 years.

Besides, the profits generated by existing customers tend to accelerate over time. Reichheld [2] attributed the acceleration in customers' profits to various reasons; such as, lower costs and efforts for serving existing customers, cross-selling opportunities, referrals and possible customer loyalty.

On the Internet, traffic is related to sales growth in two ways: through direct consumer purchases from e-commerce sites and other vendors, and through advertising revenues, paid by third parties seeking to gain exposure to the traffic which a website generates [13].

As mentioned earlier, CRM manages the relationship with customers by employing up-to-date Information Technology (IT) such as on-line data analysis, data-mining and database management in order to understand, communicate with, and to attract them. Its objective is to satisfy and retain customers [3].

It is generally accepted that database technology is the cornerstone in CRM and the success of any marketing campaign depends on the quality and structure of the databases used. According to Roberts and Berger [14], a database contains information about customers and prospects that have been collected over a considerable period of time and this database can affect all aspects of marketing effort. A database can have various tactical and strategic uses indifferent marketing variables such as product, price, promotion, channels, customer acquisition, customer service, sales force, customer relationship maintenance and marketing research.

The results of a research made by Stone et al. (2001) in [1], shows that the data within CRM systems are used for marketing applications as follows:

- Targeted marketing, 80%;
- Segmentation, 65%;
- Keeping the right customers, 47.55;
- Trend analysis, 45%;
- Increased loyalty, 42.5%;
- Customized offers, 32.5%;
- Increase share of customers, 27.5%
- The same research shows the types of data that are held, together with the frequency of usage as follows:
- Basic customer information (75%);
- Campaign history (62.5%);
- Purchase patterns (sales histories) (50%);
- Market information (42.5%)
- Competitor information (42.5%);
- Forecasts (25%).

According to [15], there are two possible sources of data: internal and external. Most companies already have the basic information needed to start a database: order and invoice information, such as customer names, addresses, account numbers, purchase data, method of payment, etc. these customer files are internal data which may be the first basis to start up a database. External data are all types of lists compiled outside the company which can be bought or hired. Examples are subscriber lists of newspapers and magazines, or databases segmented on life-style and consumption habits. As the above figures show, most of the data held in CRM systems deal with information about the customers rather than information from the customers; however, in current business environment having knowledge from customers, which directly affects loyalty, is more critical to the competitiveness of business organizations.

Customer loyalty expresses an intended behavior regarding the company which is superior to

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satisfaction. Uncles et al. ([16]) define customer loyalty as "a customer's commitment to do business with a particular corporation, buying their products and services frequently and recommending the corporation's offerings to friends and associates. According to [2], sustainable loyalty is indicated by high repeat patronage and a high relative attitude towards the company.

At the highest level of attachment, these customers are proud to be associated with the institution and take pleasure in sharing their satisfaction with others, becoming vocal advocates for the institution's products and services. Therefore, identifying loyal customers is of high value to business organizations. Moreover, in a broad market it is almost impossible for a company to serve all its customers. In this regard, business organizations apply various market segmentation strategies.

According to [17], market segmentation is a process of dividing a broad market into different and smaller groups, market segments, based on similar characteristics of customers. In the following section, Customer Lifetime Value (CLV), an effective metric for customer segmentation, will be reviewed.

2.2. Customer Lifetime Value

The key to generating high customer loyalty is to deliver high customer value [17]. Customer value has been studied under the name of Customer Lifetime Value (CLV), Customer Equity and Customer Profitability. In the realm of designation and allocation of budgets for customer acquisition, retention and related decision areas such as segmentation, gauging customer lifetime value (CLV), has always been a cornerstone.

This mainstay concept has been studied by many of researches ([7]; [14]; [18]; [19]; [20]; [21]; [22]; [23]; [24]; [25]). Berger and Nasr ([20]) define CLV as "The net profit or loss to the firm from a customer over the entire life of transactions of that customer with the firm."

According to [17], a profitable customer is a person, household, or company that over time yields a revenue stream that exceeds an acceptable amount the company's cost stream of attracting, selling, and servicing that customer in her lifetime.

Customer lifetime value is a way of measuring how much customers are worth to a corporation, over the length of time that they are considered to be the corporation's customers. The lifetime for customers will vary from industry to industry and from brand to brand [7]. The lifetime of customers comes to an end when their contribution becomes so small to be significant, unless steps are taken to revitalize them.

In this regard, extending customer life cycles has to be taken into consideration. Studies show that extending customer life cycles by three years trebles profits per customer.

Most of the studies in the field of CLV focus on Net Present Value (NPV). Mainly, the CLV models proposed so far stem from the basic equation. The basic equation is as follows:

$$CLV = \sum_{i=1}^{n} \frac{\left(R_j - C_J\right)}{\left(1+d\right)i - 05} \tag{1}$$

where i is the period of cash flow from customer transactions, R_i the revenue from the customer in period i, C_i the total cost of generating the revenue R_i in period i, n is the total number of periods of projected life of the customer under consideration, and d is the rate of return.

Therefore, the numerator is the net profit that has been obtained at each period while the denominator transforms the net profit value into the current value [16]. In this model, it is assumed that all cash flows take place at the end of a time period.

Various models have been developed for measuring CLV. In this paper a simple, yet inclusive method proposed by Hughes ([26]); namely, RFM, will be applied.

The RFM technique is an applicable methodology which has been widely-used for more than 50 years by direct marketers for segmentation purposes and consumer behavior prediction.

This technique is based on three key elements in customer behavior: Recency of purchase, Frequency of purchase and Monetary value of purchase. RFM is considered to be one of the most powerful techniques available to database marketing.

Various approaches have been developed for evaluating CLV via RFM. In a methodology presented in [26], each of the three RFM attributes is binned independently into five classes of equal size according to customer records.

Hughes [26] also suggests that in cases where the customer base is too small to be divided into five bins, fewer bins could be used. However, some authors believe that the bins need not be of equal size according to customer records and that the bins should be formed based on the relevant values of R, F and M ([14]; [27]). In this study, three bins have been considered in the model.

Another issue of controversy among the researches has been the relevant weights of the RFM variables. Hughes ([26]) claims that Recency of purchase is of greater importance than Frequency of purchase and that the Monetary value has the least important of all. Meanwhile, logically, that the RFM variables should have different weights depending on industry characteristics. Therefore, in this paper the approach presented in [27] will be applied which applies the AHP method to determine the relative weights of the RFM variables.

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2.3. Knowledge Management

One of the most common ways to describe knowledge is to distinguish it from data and information. Data can be classified as raw numbers, images, words, and sounds derived from observation or measurement. Information represents data arranged in a meaningful pattern. Unlike information, knowledge is about beliefs, commitment, perspectives, intention and action [28].

A simple, yet comprehensive definition of knowledge provided by Davenport and Prusak ([29]) is as follows: Knowledge is a fluid mix of framed experience, values, contextual information, expert insight and grounded intuition that provides an environment and framework for evaluating and incorporating new experiences and information. It originates and is applied in the minds of knowers. In organizations, it often becomes embedded not only in documents or repositories but also in organizational routines, processes, practices, and norms." Knowledge management (KM) is an emerging field that has gained prominent popularity among organizations to succeed in the current competitive business era. According to [30], KM is management of a company's corporate knowledge and information assets to provide this knowledge to as many company staff members as possible as well as its business processes to encourage better and more consistent decision-making.

Knowledge management is concerned with ensuring that the right knowledge is available in the right form to the right processor at the right time for the right cost [31].

Some other researches (e.g., [32]) have even defined KM more broadly as a fast-moving field created by the collision of several others, including human resources, organizational development, change management, information technology, brand and reputation management, performance measurement, and evaluation.

Knowledge management enables CRM to expand from its current "mechanistic, technology-driven, data-oriented approach" towards more holistic, complex and insightful ways of developing and using customer knowledge [33].

Many authors categorize knowledge into tacit and explicit ([34]; [35]). Explicit knowledge, as codified knowledge, is transmittable in formal, systematic language; and tacit knowledge is personal, context-specific, and difficult to formalize and codify. Tacit knowledge is personal in origin, job specific, related to context, difficult to fully articulate, difficult to document or categorize and is non-financially tangible.

2.4. Customer Knowledge Management

By integrating operational CRM data with knowledge from around the enterprise, companies can make use of the abilities of analytical CRM systems, and with them, make truly customer centric business decisions. For example, companies can proactively offer products and services that fit a given customer's needs based on what the customer has already purchased, or increase purchase rates by dynamically personalizing content based on Web visitor's profile, or provide customers in the highest value tier with personal representatives who understand their history or preferences [36].

According to [17], CRM is a high-tech way of gathering mountains of information about customers, then using it to make customers happy—or at least a source of more business. It is therefore, concerned with understanding and influencing customer behavior.

True CRM is possible only by integrating them with KM systems to create knowledge-enabled CRM processes that allow companies to evaluate key business measures such as customer satisfaction, customer profitability, or customer loyalty to support their business decisions. Such systems will help marketers address customer needs based on what the marketers know about their customers, rather than on a mass generalization of the characteristics of customers [36].

CKM has drawn much attention by the combining of both the technology - driven and data - oriented approaches in CRM and the people-oriented approach in KM, with a view to exploit their synergy potential [37].

Kotler ([17]) classifies knowledge into three major categories:

- Knowledge 'for' customers satisfies customers' requirements for knowledge about products, the market, and other relevant items.
- Knowledge 'about' customers captures customers' background, motivation, expectation, and preference for products or services.
- Knowledge 'from' customers understands customers' needs pattern and/or consumption experience of products and/or services.

CKM is contrasted with knowledge about customers, e.g. customer characteristics and preferences prevalent in previous work on knowledge management and customer relationship management [38]. CKM deals not only with customer experience and satisfaction, but also with collaboration with them for joint value creation. In this regard, performance of the business organization is evaluated against competitors in innovation and growth and contribution to customer success.

2.5. Corporate Image

It is widely accepted that corporate reputation and corporate image have the potential to impact on customer loyalty toward the business organization.

Corporate image is described as the overall impression made on the minds of the public about a firm ([17]), and is related to the various physical and behavioral attributes of the firm, such as business name,

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architecture, variety of products/services, tradition, ideology, and to the impression of quality communicated by each person interacting with the firm's clients [39]. Specifically, a corporation's image includes the perceptions of all stakeholders such as; suppliers, customers, shareholders, employees and the community, noticing that each stakeholder needs to be addressed separately through the firm's communication strategy [40]. Researchers have recognized that a firm's reputation is a valuable intangible asset that requires a long-term investment of resources, efforts, and attention to customer relationships.

As noted by Lemmink et al., ([41]), image consists of several factors that influence the behavior of individuals towards the object. However, the set of factors used to evaluate the object will be different for each individual.

Corporate reputation may be viewed as a mirror of the firm's history which serves to communicate to its target groups information regarding the quality of its products or services in comparison with those of its competitors [42]. Reputable companies seem to have more stable revenues, generate more loyalty and productivity from their employees, and have lower risks of crisis [43].

Furthermore, reputable online organizations attract more media exposure. A research by Kotha et al., ([13]) shows that the more media exposure an Internet firm gets in the form of articles published about it in the media, the higher will be its sales growth. They also claim that on the Internet, the focus of consumer attention helps generate traffic to a firm's website where customers surf and examine a website because they are aware of it, by virtue of its media exposure.

Corporate image and reputation have a direct effect on customer trust. According to [44], trust is a critical factor in stimulating purchases over the Internet and has a vital influence on consumer activities and thereby on e-commerce success. As a study by Teo and Liu ([45]) shows, in Internet shopping, perceived reputation of a vendor is significantly related to consumers' trust in the vendor. However, some researchers (e.g., [46]) suggest that some customers have trust in a company although the company might not be highly reputable.

3. Proposed Model

The proposed model tries to provide a framework for the application of CKM and CRM data in segmenting the customer base.

As shown in Figure 1, initially, the general customer purchase information is used to measure customer present value. This information includes the RFM data; namely, Recency of purchase, Frequency of purchase, and Monetary value of purchase. Then, as discussed earlier, in order to give relative weights to RFM parameters, the Analytical Hierarchy Approach (AHP) is applied. Finally, using a Multi-layered Feed-forward Neural Network (MFNN) model, the present value of customers is measured. This part of the model, involves knowledge *for* the customer. Thereafter, future customer value is estimated, using knowledge *about* customers. Here, various socio-demographic data are taken into consideration; which according to [17], could include, Geographic (e.g., Region, City, Density, Climate, etc.), Demographic (e.g., Age, family size, family life cycle, Gender, Income, Occupation, Education, Religion, Race, Generation, Nationality, Social class, etc.), Psychographic (e.g., Lifestyle, Personality, etc.) and Behavioral (e.g., Occasions, Benefits, User status, Usage rate, Loyalty status, Readiness stage, Attitude toward product, etc.) data.

As mentioned earlier, acquiring knowledge *from* customers is the most critical task that affect competitiveness. In this regard, customer knowledge data is used to measure corporate image and reputation, and customer satisfaction. Then, again using a MFNN model, customer future value is estimated. Finally, taking into account customer present and future values, the customer base is segmented using a Decision-Tree algorithm.

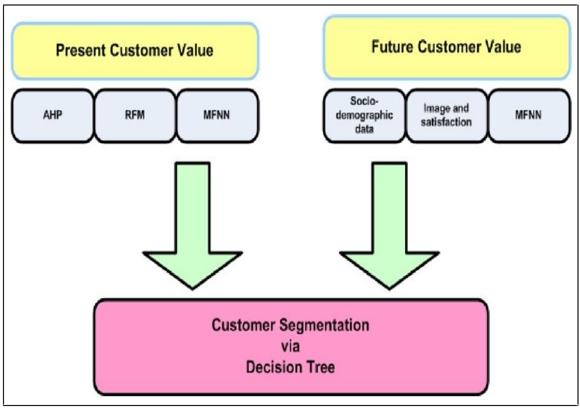

Fig. 1. Proposed model for customer segmentation

4. Case study

The case study was performed on an online movie retailer. A data set consisting of 715 customers was available; however, 92 customers were excluded due to lack of information or due to MFNN requirements. Therefore, a customer base of 623 was considered in the study.

4.1. Measuring Present Customer Value

As mentioned earlier, in this study, the weighted RFM model is applied for measuring the present value. First of all, the AHP, method was used to calculate the relative weights of the RFM parameters. In this case, 10 experts; including the retailer managers and e-commerce specialists were asked to do pair-wise comparisons between the parameters. The result of the survey is illustrated in Figure 2. Then, the consistency index of the values was calculated as 0.0005, which significantly falls below the acceptable threshold value. Finally, the relative weights of the RFM parameters are calculated as 0.109, 0.309, and 0.582 respectively.

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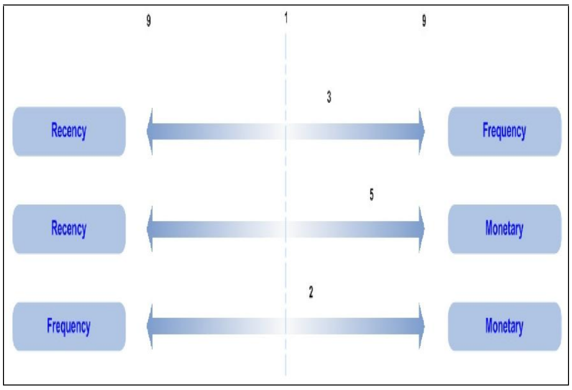

Fig. 2. AHP weighting scale

Thereafter, according to the calculated weights, the RFM Analysis could be performed for each customer. In this regard, the maximum possible RFM value could be $0.109 \cdot R + 0.309 \cdot F + 0.581 \cdot M = 3$. In this study, the RFM value was regarded as a metric of the present value of customers. Thus, the customers having a minimum of 80% of the maximum RFM value were considered as *high-value*, customers whose RFM value was between 40% to 80% of the maximum value were considered as *medium-value* and the remaining customers were regarded as *low-value.*

Finally, a Multilayer Feed-forward Neural Networks (MFNN) is used to classify customers regarding their RFM value. For this purpose, an add-in software for Neural Networks was applied in Microsoft Excel. Neural networks are simple computational tools for examining data and developing models that help to identify interesting patterns or structures in the data. The data regarding the RFM of purchase were considered as the model input and were defined as categorical data as they were binned into 3 specific classes while the ratio of RFM value to the maximum possible weighted RFM value of customers was regarded as the model output. The model was run for 25 times and the parameters were modified each time. The best possible parameter sets are listed in Table 1.

Tab. 1. Parameter settings for MFNN in the customer present value model

Parameter	Details
Number of inputs	4
Number of hidden layers	2
Learning parameter	0.8
Momentum	0.3
Initial weight range	0.3
Number of training cycles	40
Random input order to the model	YES
Training/Validation ratio	Random 10%
Training mode	Sequential
Number of Training observations	560
Number of Validation observations	63

The confusion matrices for the training and validation sets are shown in Figure 3.

Confusion Matrix - Training set

TRUE	Predicted high	Predicted medium	Predicted low
high	115	16	1
medium	69	230	40
low	0	0	89

Confusion Matrix - Validation

TRUE	Predicted high	Predicted medium	Predicted low
high	7	1	0
medium	7	30	2
low	0	0	16

Fig. 3. Confusion matrices for the training and validation sets in the customer present value model

As we can see, in the training set, 109 medium-classed customers were misclassified by the model. However, the MSE values were calculated for the training and validation sets. The MSE results are shown in Figure 4.

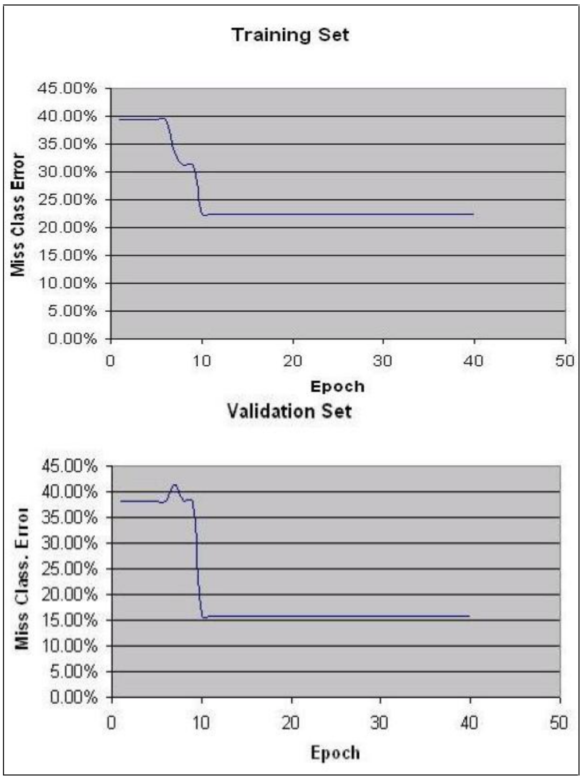

Fig. 4. MSE values in the customer present value MFNN model

It could be noticed that the minimum MSE value was resulted in the 10th training cycle.

As another metric of the model accuracy, the lift chart is provided in Figure 5.

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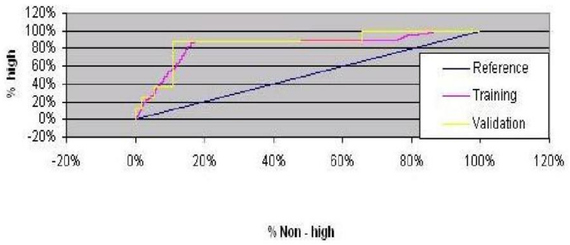

Fig. 5. Lift chart for the present value model

4.2. Predicting future value of customers

At this stage a MFNN model is used to predict customer value. Here, various knowledge from the customers are taken into consideration. Also, in order to maximize the level of model's comprehensiveness, other critical variables affecting the lifetime value of customers were included in the model. Customer satisfaction and corporate image perception of customers were taken as input variables for. In our study, main contributors to customer satisfaction were: quality of service/product provided, delivery, price, ease of navigation, design of the website, search engines, ease of access (availability) of the website, rich and up-to-date archive, and security Also, as discussed earlier, corporate image is a decisive parameter in customer's future buying intentions and loyalty. Therefore, this knowledge *from* the customers was included as a major contributor to the future value in this model. The factors affecting the image in this study were: branding parameters (logo, slogan, design, advertising and links to the site), technical awards, number of hits, leadership reputation, and donation to charities and other humanitarian and environmental responsibilities and contributions.

Tab. 2. Parameter settings for MFNN in the customer future value model

Parameter	Details
Number of inputs	12
Number of hidden layers	2
Learning parameter	0.8
Momentum	0.2
Initial weight range	0.9
Number of training cycles	40
Random input order to the model	YES
Training/Validation ratio	Random 10%
Training mode	Sequential
Number of Training observations	560
Number of Validation observations	63

Other parameters included in the model were the total number of products purchased, recency of purchase, frequency of purchase, total amount of money spent and category of products purchased. Also, socio-demographic parameters were taken into consideration; namely, age, sex, region, and income.

The model was run 25 times to identify the best parameter settings. All parameter settings are listed in Table 2 and the MSE values in the training and validation set are shown in Figure 6.

This model classifies the customers into High, Medium and Low categories according to their predicted future value.

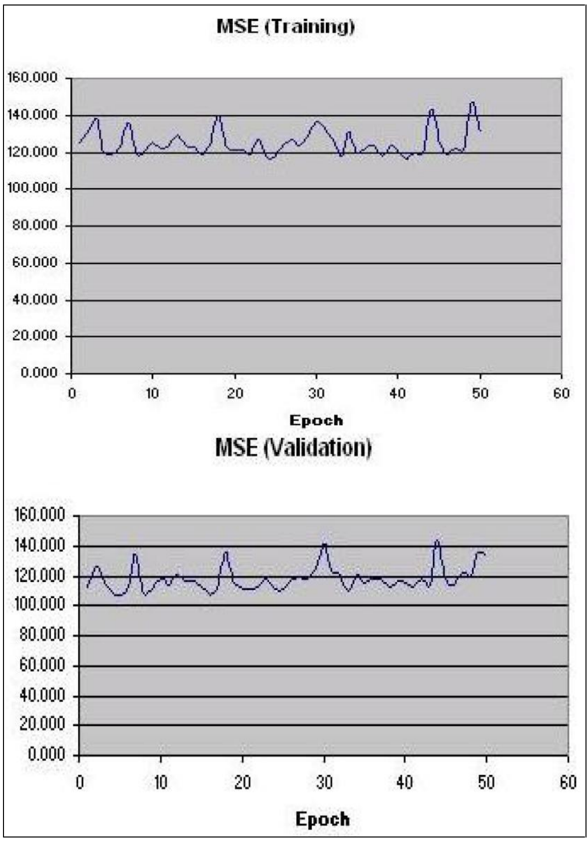

Fig. 6. MSE values in the customer future value MFNN model

4.3 Segmenting Customers

In order to segment the customer base, a Decision Tree algorithm was applied in the model. The inputs to this model were the customer present and future values resulted from the previous sections. The parameter settings and the rule-text for the Decision Tree are shown in Table 3 and Figure 7 respectively.

The methodology used here was the Multi-tier segmentation model which classifies the customers into five categories: Platinum, Gold, Silver, Iron, and Lead.

In this case, Platinum segment refers to the customers whose present and predicted future values are High and are regarded as high value customers whose profits to the company is predicted to grow over time. These customers are highly committed to the company so the main policy for management is to retain such customers and keep them loyal.

The Gold segment refers to customers whose present value is high (or medium) and their potential value is medium (or high). Such customers are always potential Platinum customers. They have a high level of loyalty

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to the company and are not willing to switch to competitors so these customers should be retained for the company and special programs should be applied to shift (or keep) them to the Platinum tier.

```
Rule0            Segment = silver

Rule1      IF    Potential Value = high
           AND   Present Value = high
           THEN  Segment = platinum

Rule2      IF    Potential Value = high
           AND   Present Value = medium
           THEN  Segment = gold

Rule3      IF    Potential Value = low
           AND   Present Value = high
           THEN  Segment = silver

Rule4      IF    Potential Value = low
           AND   Present Value = low
           THEN  Segment = lead

Rule5      IF    Potential Value = low
           AND   Present Value = medium
           THEN  Segment = iron

Rule6      IF    Potential Value = medium
           AND   Present Value = high
           THEN  Segment = gold

Rule7      IF    Potential Value = medium
           THEN  Segment = silver

Rule8      IF    Potential Value = medium
           AND   Present Value = medium
           THEN  Segment = silver
```

Fig. 7. Rule-text for the Decision Tree

Training Data

Predicted Class

True Class	gold	iron	lead	platinum	silver	
gold	46					46
iron		18				18
lead			58			58
platinum				105		105
silver					334	334
	46	18	58	105	334	561

Test Data

Predicted Class

True Class	gold	iron	lead	platinum	silver	
gold	2					2
iron		1				1
lead			2			2
platinum				11		11
silver					46	46
	2	1	2	11	46	62

Fig. 8. Confusion matrices for the training and test sets in the Decision Tree

Silver customers are fairly loyal customers of the company whose costs to the company do not exceed their profits. These customers-who are the major customers of the company-should be retained and special loyalty programs and other initiative such as purchase discounts should be applied to shift them to the Gold segment.

The Iron segment refers to customers whose present (or future) value is medium but future (or present) value is low. The level of loyalty and profitability of such customers is not so significant to be treated specially.

Tab. 3. Parameter settings for the Decision Tree

Parameter	Details
Total number of nodes	12
Number of Leaf Nodes	9
Number of Levels	3
% Misclassified on training	0%
% Misclassified on test	0%
Number of predictors	2
Number of Classes	5

The Lead segment refers to customers whose cost to the firm exceeds their profits and who are apt to switch to competitors. Such customers are not worth retaining and the only strategy regarding them is to prevent them from negative word-of-mouth.

The confusion matrices are provided in Figure 8.

Other segmentation results are provided in Table 4. The values for Support, Confidence and Capture are provided for measuring the precision level of the decision tree. Support reflects the percentage of the training data for which the rule is true. In other words, it measures how widely applicable the rule is.

Confidence reflects the level of accuracy of the rule. Capture refers to the observations correctly classified in a segment. If there is a rule with Capture close to 100%, it indicates that, in the predictor space, all observations with this class sit closely to each other and the rule has been able to capture that part of the predictor space very well.

Tab. 4. Segmentation results

Rule ID	Class	Length	Support (%)	Confidence (%)
0	Sliver	0	100.0	59.5
1	Platinum	2	4.1	100.0
2	Gold	2	4.1	100.0
3	Silver	2	0.2	100.0
4	Lead	2	10.3	100.0
5	Iron	2	3.2	100.0
6	Gold	2	4.1	100.0
7	Silver	1	63.5	93.5
8	Silver	2	52.4	100.0

5. Conclusion

The aim of this paper was to provide a framework for the application of CKM in real-world marketing

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environment. After an overview of the literature, a model was proposed for customer segmentation based on customer present value and predicted customer future value. For measuring the customer present value, a MFNN model was applied considering the weighted RFM values calculated via the AHP methodology. Future value was estimated by taking into account various knowledge *from* the customers; such as, corporate image and reputation, and customer satisfaction. Also, socio-demographic parameters were included in the model for further accuracy. Finally, the customer base was segmented using a Decision Tree algorithm regarding present and future values. With such segmentation strategy, business organizations can better identify their valuable customers and remain competitive by

having knowledge *from* them; especially, in the realm of the online business environment where the competitors are just a click away and the switch cost are minimum for the customers. However, there were several limitations to the study. First of all, the case study was done on an e-retailer whereas, in other sectors, the results might be different. Also, the AHP method, although very applicable, has been criticized by some authors for being biased in some cases. Furthermore, other statistical methods could be applied in comparison with the artificial neural networks applied in this study.

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