CHAPTER 2
LITERATURE SURVEY

An extensive literature survey is carried out as part of this research in order to analyze the profiling methodology using data mining techniques. The profiling methodology is based on customer lifetime value, relationship, satisfaction and behavior using data mining techniques.

2.1 OBJECTIVES OF CRM

The new marketing paradigm is based on knowledge and experience, Payne and Frow (2006). Knowledge-based marketing paradigm indicates that corporations need to know more about customers; and an experience-based marketing paradigm suggests bringing more interactions into customer related activities. Parvatiyar and Sheth (2001) defined CRM as “a comprehensive strategy and process of acquiring, retaining, and partnering with selective customers to create superior value for the company and the customer”. From the architecture point of view, the CRM framework can be classified into operational and analytical, He et al. (2004), Teo et al. (2006). Operational CRM refers to the automation of business processes, whereas analytical CRM refers to the analysis of customer characteristics and behavior so as to support the organization’s customer management strategies. As such, analytical CRM could help an organization to better discriminate and more effectively allocate resources to the most profitable group of customers. According to Parvatiyar and Sheth (2001), Kracklauer et al. (2004), CRM consists of four dimensions:

(1) Customer Identification.
(2) Customer Attraction.
(3) Customer Retention.
(4) Customer Development.

These four dimensions can be seen as a closed cycle of a customer management system, Au and Chan (2003), Kracklauer et al. (2004), Ling and Yen (2001). Since 90s, there have arisen numerous synonymous terms: customer management, customer information systems, customer value management, customer care and sometimes customer centricity or customer-centric management, but now clearly, the term Customer Relationship Management has become the most widely used, Lee and Kim (2008). In today’s competitive era, customer
relationship management can be adopted as a core business strategy in order to help organizations manage customer interactions more effectively, Mishra and Mishra (2009).

The central objective of CRM is thus to maximize the lifetime value of a customer to the organization, Peppard (2000). CRM is an interactive process that turns customer information into customer relationships through actively using and learning from information. It is a cycle for encompassing major group of actions: knowledge discovery, market planning, customer interaction, and analysis refinement. Successful implementation of CRM requires cross-functional reorganization, especially marketing and information technology, to work closely together to maximize the return on customer information. Ryals and Knox (2001) determined that the philosophical bases of CRM are: relationship orientation, customer retention, and superior customer value created through process management. Wu et al. (2005) used decision rules and data mining to investigate the potential customers for an existing or new insurance product. These methods enable companies to invest in customers who will produce the most profit for the company.

An on-going relationship with customers will help in providing a sense of security, trust and feeling of control. The characteristics of well working CRM are as follows:

- Increased customer satisfaction.
- Provide information on future sales.
- To meet customers’ needs in a better way.

Through studies, Xu and Walton (2005) have concluded that the major reasons corporation managers implementing CRM are:

- Customer satisfaction.
- Retain existing customers.
- Provide strategic information.
- Improve Customer Lifetime Value.

The general objectives of CRM systems are to collect data about customer interactions with the firm, Nguyen et al. (2007). They also state these points as more specific objectives:
• **Increased Customer Loyalty**
  Collecting all important information about a customer and having all the relevant data about customer’s history readily available at all access points in the organization.

• **Superior information gathering and knowledge sharing**
  The CRM system updates the history of each customer as soon as an interaction occurs, no matter how the interaction took place, whether it is through, Sales, Support or the web site.

• **Understanding customers**
  Analytical CRM can further be used to build predictions of trends and try to forecast demand, as well as to better understand each individual customer and thus providing a better offer to the customer.

• **Superior Service**
  Using information about customer’s habits and interactions with the firm to offer relevant products and services customized to each customer.

### 2.2 CONTENT ANALYSIS

Content analysis is the process of establishing a framework and selecting the units of analysis based on the goal of the study. It uses the principles of “measurable” and “quantifiable” to design categories that can partition the analyzed units’ data content into a series, selects representative data samples, and uses the categories to quantify (recording coding decisions and performing reliability analyses) and analyze the samples.

Empirical studies in traditional communication fields often use content analysis on various style of advertisement; in computer-mediated communications, content analysis has been used to analyze discussions in newsgroups and on electronic bulletin boards. Data mining extracts accurate, previously unknown, yet significant information from large databases and uses this information to make important decisions.

### 2.3 CUSTOMER LIFETIME VALUE ANALYSIS

Miglautsch (2000) states that Customer Lifetime Value models are used widely to identify customer loyalty and determinate marketing strategies to different groups of customers. Customer lifetime value analysis is defined as the prediction of the total net income a company can expect from a customer, Drew et al. (2001), Etzion et al. (2005),
Rosset et al. (2003). Customer lifetime value using Recency, Frequency and Monetary (RFM) method is used to find target customers. Customer data usually consists of many variables. There is a large amount of research that suggests RFM variables appear to be a good source for predicting customer behavior. Recency variables store information regarding the timeframe between purchases or use of service. A lower value suggests a higher probability of the customer making a repeat purchases. Frequency variables are those connected to how often the service is used. In general, it can be assumed that the higher the frequency, the more satisfied the customer is with the service. A monetary variable for a customer would be the total sum of money a customer spends on his/her services over a certain time period. Those customers with high monetary values are the ones and organization should be most interested in retaining.

For weighting RFM variables, AHP as one of the most applicable Multi-Criteria Decision Making (MCDM) methods has been used by various researchers, Weiwen et al. (2008). CLV models are used widely to identify customer loyalty and determinate marketing strategies to different groups of customers. There are several models for CLV. Some of them are based on past behavioral models and some of are based on future customer revenue.

Past Customer Value (PCV) is another CLV model based on the past monetary value of customers. PCV extrapolates the past monetary spent by customers in past purchases into present time. This model doesn’t consider the future expected customer value. Some Life Time Value (LTV) models, consider future monetary value of customers prospect the future monetary value of customers. These models extrapolate the future prospected monetary will spend by customer into present time. Glady et al. (2009) has prospected future customer acquisition profits and active time for each customer, and then they have sued them to estimate the LTV. CLV is the present value of all future profits for firms generated from a customer, Gupta and Lehmann (2003). Calculating CLV has lots of applications and several authors have developed models for different applications such as performance measurement, Rust et al. (2004), targeting customers, Haenlein (2006), marketing resources allocation, Reinartz et al. (2005), Sublaban et al. (2009), product offering, Shih and Liu (2007), pricing, Hidalgo et al. (2007), and customer segmentation, Kim et al. (2006), Haenlien (2007). Pfeifer et al. (2005) defined CLV as the present value of the future cash flows attributed to the customer relationship and finally Sublaban and Aranha (2009) described CLV as estimated monetary value that the client will bring to the firm during the entire lifespan of his/her commercial relationship with the company, discounted to today value. In Liu and
Shih (2007) study, recency is the most important parameter and Monetary is the less important parameter, but in Chuang and Shen (2008) study, Monetary has the most value and Recency had the least value.

When considering the key components of the process of measuring and managing CLV, Kumar et al. (2004) focus on customer acquisition and retention. Keymak (2001) believes that RFM model is one of the known methods for analyzing customer value. The most important characteristic of RFM is simplicity and speed of its implementation, McCarty and Hastak (2007). Lin and Tang (2006) also applied RFM model to analyze customers of music product. Lo et al. (2008) adopted RFM model to analyze members of a sports store. The results showed that higher expense customers are male and aged from 26 to 35. Huang et al. (2009) applied K-means method, Fuzzy C-means clustering method and bagged clustering algorithm to analyze customer value for hunting store in Taiwan and finally concluded that bagged clustering algorithm outperforms the other two methods. Baesens et al. (2002) combined RFM analysis with Bayesian neural networks, and introduced a method to forecast purchases in European companies.

2.4 CUSTOMER SATISFACTION AND RELATIONSHIP

Satisfaction is really a gap measure between performance and expectation. A completely satisfied customer perceives their service to meet or exceed expectation, Kim et al. (2004). Finding a suitable measurement of customer satisfaction is a major problem for organizations. The importance of customer satisfaction has been accepted, and has received attention from researchers across multiple service sectors. Some examples include determining customer satisfaction levels in the context of online retailing, Hsu (2008), Souitaris and Balabanis (2007), Construction Project Management (CPM) which is a technically an oriented service for construction project clients Yang and Peng (2008), and customer satisfaction levels within the telecommunications industry Eshghi et al. (2007).

Companies should be continuously improving their products and services to retain and enhance customer satisfaction; however customer satisfaction can suffer from other areas of business such as customer service, billing problems and faults. Seeking to maintain customer satisfaction through a product-based approach alone is insufficient. Improving the range of products and enhancing services does not necessarily improve customer satisfaction levels, however poor product availability and bad service can have a high negative impact on customer satisfaction levels (Conklin et al. 2004). This suggests that although services and
technologies need to be up-to-date from a strategic point of view, service errors are more damaging than service upgrades are rewarding, in terms of existing customer perceptions.

Customer loyalty is regarded in industry to be different to customer satisfaction. Loyal customers have been described as customers who show a psychological reaction and conviction to a specific product or service experience. Loyal customers are believed to possess a positive mental attitude towards their service provider, executing a continued repurchase conduct, Mankila (2004). Customer loyalty is not a new concept in business. The literature identifies two types of satisfactions: transactional and overall satisfaction (or cumulative satisfaction). Transactional satisfaction is defined as post choice evaluative judgment of a specific purchase occasion, whereas cumulative customer satisfaction is an overall evaluation based on the total experience.

The concept of customer loyalty has received multiple definitions and interpretations. Researchers holding a deterministic view, generally regard loyalty from an attitudinal perspective, while researchers holding a stochastic view tend to regard loyalty from a behavioral perspective. For example, word of mouth has been used in some cases as a dimension of loyalty by some researchers and an outcome of loyalty by others. Researchers have since taken the view of combining both loyalty views, to create a multidimensional view of loyalty, including a broad range of loyal states to benefit both the customer and the marketer. Examples of the dimensions of loyalty are as follows:

**Situational Loyalty** - It has been regarded that loyalty could be the result of situations faced over time, and as a tendency for a person to exhibit similar behavior. To elaborate, situational loyalty is the understanding that customers purchase products depending on the situation, such as purchasing a gift for an anniversary etc.

**Resistance to competing offers** - Occurring when customers are resistant to, or protected from other competing offers. One example of a customer that would be resistant would be a customer who is contracted to a supplier, making them unable to respond to competing offers. The relationship between resistance to competing offers and loyalty is still unclear. Again, some researchers regard resistance to competing offers as a dimension of loyalty, while others regard it as a consequence.
Propensity to be loyal - Measuring loyalty as a personal trait. Propensity to be loyal is regarded as an important measure for marketers, because it is regarded that it can sound the alarm for a decline in other loyal states.

Attitudinal Loyalty - Measures of attitudinal loyalty include preference, intention to repurchase, and commitment. Attitudinal loyalty is usually used for predicting behavior. Word of mouth has been used by some research as a measure of attitudinal loyalty.

Complaining Behavior - It may appear strange to include complaining behavior as an aspect of customer loyalty, however researchers view complaining behavior as ‘the customer using his/her voice’, and it is regarded that complaints can provide positive feedback to a company as well as negative.

Customer satisfaction is a multidimensional construct that is a direct result of the multiplicity and divergence of the contextual effects of customer expectations. According to Souitaris and Balabanis (2007), customer loyalty is a key driver of sustainable profitability and growth. Customer satisfaction, which refers to the comparison of customers’ expectations with his or her perception of being satisfied, is the essential condition for retaining customers, Kracklauer et al. (2004). As such, elements of customer retention include one-to-one marketing, loyalty programs and complaints management. One-to-one marketing refers to personalized marketing campaigns, which are supported by analyzing, detecting and predicting changes in customer behaviors, Jiang and Tuzhilin (2006).

The core part of CRM activities is to understand customer requirements and retain profitable customers. To reach it in a highly competitive market, satisfying customer’s needs is the key to business success, Kengpol (2006). Data mining methodology has a tremendous contribution for researchers to extract the hidden knowledge and information, which have been inherited in the data used by researchers, Seyed Mohammad Seyed Hosseini et al. (2010). Data mining has a tremendous contribution to the extraction of knowledge and information, which have been hidden in a large volume of data, Beomsoo Shim et al. (2012). The concept of Customer Satisfaction and Loyalty (CS & L) has attracted much attention in recent years. A key motivation for the fast growing emphasis on CS & L can be attributed to the fact that higher customer satisfaction and loyalty can lead to stronger competitive position resulting in larger market share and profitability, Erkan Bayraktar et al. (2011).
The expert system’s role is in the preparation to capture the knowledge of the experts and the data from the customer’s requirements. In order to identify the hidden pattern of the customer’s needs, the artificial neural networks technique has been applied to classify the fragrance notes based upon a list of selected information, Athakorn Kengpol and Worrapon Wangananon (2006). The expert system’s role is in the preparation to capture the data from the customer’s requirements and predict appropriate perfume. For this end, factors of perfume costumers’ decision were recognized using fuzzy Delphi method and a back propagation neural network classification model was developed and trained with 2303 data of customers, Payam Hanafizadeh (2010).

The proposed business intelligent system for demand forecasting proves to give more accurate prediction for future demands compared to the existing models and practices in spare parts inventory management. This helps inventory managers to manage their supply chain performance better by reducing reaching days and service level simultaneously. Reaching day as a measure of inventory level is generally reduced successfully by the retailers at the cost of service level in most of the places, Pradip Kumar Bala (2010).

Ryals and Knox (2001) determined that the philosophical bases of CRM are: relationship orientation, customer retention, and superior customer value created through process management. A key challenge for companies is to manage customer relationships as an asset. To create an effective toolkit for the analysis of customer relationships, a combination of relational databases and fuzzy logic is proposed, Meier (2005). Although front end systems such as advertising, public relations letter and promotional items, an organization must be willing to in build and maintain relationships with existing customers. It is vital to have the organizations name known to existing and potential clients, Bolton et al. (2000).

**2.5 CUSTOMER BEHAVIOR USING CLUSTERING AND ASSOCIATION RULES**

Data mining techniques are deeply being applied in business. The term data mining grew from the relentless growth of techniques used to interrogation masses of data, Dawn et al. (2012). This work is based on association rule mining and clustering, which are among the frequently used approaches so far. Carrier and Povel (2003), Mitra et al. (2002), Shaw et al. (2001) described the types of data mining model as Association, Classification, Clustering, Forecasting, Regression, Sequence Discovery and Visualization. Knowledge Discovery in Database (KDD) or data mining is an approach that is now receiving great
attention and is being recognized as a newly emerging analysis tool, Ismail et al. (2010). K-means, kohonen network/self organizing map, two step, and Fuzzy C-means are some of the modeling techniques for clustering, Rad et al. (2011).

Clustering analysis is a data mining technique that maps data objects into unknown groups of objects with high similarity. Clustering algorithms are classified into partitional or hierarchical. Clustering is the task of segmenting a heterogeneous population into a number of more homogenous clusters, Ngai et al. (2009). Clustering is the task of segmenting a heterogeneous population into a number of more homogenous clusters, Ahmed (2004), Berry and Linoff (2004). A cluster is therefore a collection of objects, which are “similar” between them and are “dissimilar” to the objects belonging to other clusters. So, the goal of clustering is to determine the intrinsic grouping in a set of unlabeled data. Good clustering can be shown that there is no absolute “best” criterion, which would be independent of the final aim of the clustering. Consequently, it is the user, which must supply this criterion, in such a way that the result of the clustering will suit their needs. For instance, we could be interested in finding representatives for homogeneous groups (data reduction), in finding “natural clusters” and describe their unknown properties (“natural” data types), in finding useful and suitable groupings (“useful” data classes) or in finding unusual data objects (outlier detection).

Association rules are useful for the analysis of customer data, Beomsoo Shim et al. (2012). An association rule can be represented in the form \( X \implies Y \), indicating that when product \( X \) is purchased, product \( Y \) is also purchased. \( X \) is known as the antecedent and \( Y \) is the consequent, such that \( X \) triggers the purchase of \( Y \). The algorithms, which can be used for market basket analysis, are for a generic problem of association: the Apriori algorithm, Frequent Pattern (FP) growth algorithm, and Eclat algorithm, Han et al. (2000). There are two different methods for mining changes in customers' behavior. In the first method, a statistical approach was proposed to distinguish patterns that either are emerging trend or stable in different time periods, Au and Chan (2005), Böttcher et al. (2009). In the second method, patterns extracted from datasets of two different time periods are compared and changes in them are detected. Changes are detected by analysis customers' moves between clusters, Min and Han (2005).

Bhatnaga and Ghose (2004) provide a new transaction model based on service and customer satisfaction and showed that price is not the only measure that affects customer
purchasing decisions, but also it is important that customer and company agree on product value and good customer services.

2.6 CUSTOMER PROFILES

Some characteristics correlate positively with companies performing well in customer relationship management: excellent products, excellent management, and the informed use of knowledge about customers. An insufficient knowledge base of customers limits the value, which a company can offer to those customers, Tiwana (2001). Knowing customers better, a corporation can precisely invest in valuable customers and reduce the cost spent on poorly performing customers, Hwang et al. (2004). The basic component of customer knowledge comes from a customer profile that is obtained by the use of a database and data mining technologies used in organizations, Adomavicius and Tuzhilin (2001). Building customer profiles is one of the most popular strategies for knowing more about customers. In summary, using a customer profile is the technique, which converts raw information about customers into the strategic-support knowledge that reinforces the value of goods which companies offer customers.

2.7 CUSTOMER PARTICIPATION

The customer profile is a more structured part of customer knowledge; whereas a more non-structured part could come from customer participation. In the service research area, customers who contribute information or efforts in the service complete the process with the service provider. They fulfill the process together while the service is produced and consumed at the same time, Huber et al. (2007). For example, patients describe their own symptoms to doctors. It makes the process of diagnosis go more smoothly. These service performances are heavily influenced by customer efforts and the information they themselves provide.

There are different dimensions of participation, including personal interaction, information sharing, and responsible behavior. This suggests that participation has a positive impact on customer's perceived product/service quality, customer satisfaction, and a mixed impact on retention. Different aspects of participation do not contribute equally in these models. Specifically, personal interaction was found to have more significant effects while the information sharing was thought to be of particular significance from a conceptual perspective. There is a similar result in the new product development research area. It
indicates that through close interactions with customers, designers can accurately identify market requirements, quickly refine product specification, and reduce time for marketing and thus remain more competitive, Nambisan and Baron (2007).

Little CRM research has put specific effort into getting and using non-structured information about customers, Lin (2002). Customer participation can fulfill the shortage of application towards gaining tacit customer knowledge. Customer participation in the delivery of service processes has been found to be highly related to customers’ perceived quality of service, customer satisfaction and new products’ performance. Customers can contribute their own information in the process of participation and also get information about the corporation. This is a two-way communication between buyers and sellers, which positively impacts the CRM’s performance. Similar discussions are involved in a large number of different research areas. In service research, customer participation refers to the contribution of customer information and the effort spent in the process of service encounters. Customer participation influences the quality of service. In information system development research, user participation has been found to influence user’s perception of system success and user satisfaction, Wu and Marakas (2006). In advertising research, scholars look at the impact which customer involvement; advertising and products have on purchasing decisions.