"PREDICTING CUSTOMER CHURN IN THE MOBILE TELECOMMUNICATION INDUSTRY, A CASE STUDY OF MTN GHANA, KUMASI"

By

NAME:

KOJO ABIW-ABAIDOO JR

**A Thesis submitted to the Institute of Distance Learning,
Kwame Nkrumah University of Science and Technology, in partial fulfillment of the requirements for the degree of**

COMMONWEALTH EXECUTIVE MASTERS OF BUSINESS ADMINISTRATION

October, 2011

DECLARATION

I hereby declare that this thesis is the result of my own work except references cited that have been duly acknowledged. It has never been submitted for the award of any degree.

Kojo Abiw-Abaidoo Jr	………………………..	………………….
Name	**Signature**	**Date**

Certified by:

Ahmed Agyapong	…………………….	………………….
(Supervisor)	**Signature**	**Date**

Professor I. K. Dontwi	…………………….	………………….
(Dean IDL)	**Signature**	**Date**

DEDICATION

This project is dedicated to my lovely daughter, Theodocia Efua Abiw-Abaidoo.

ACKNOWLEDGEMENT

I give thanks to the Almighty God for the precious life, wisdom, guidance and strength granted me to be able to write this thesis.

To my lovely wife, Abigail thanks you for the support and sacrificing your comfort for me to be able to write this thesis.

Thanks to Isaac Aidoo for the support giving me with the data mining aspect of this thesis.

To the Marketing Division of MTN, Ghana, thanks for granting access to data

Mr. Ahmed Agyapong, my supervisor, I acknowledge the guidance and direction you gave me through the writing of this thesis.

And to anybody who in one way or the other helped me out with this thesis, God Bless You All.

ABSTRACT

Customer churn has been of much concern for companies, very active in industries where lower switching cost exists. The Telecommunication Industry is among those industries which suffer from this phenomenon, producing an annual churn rate of 30%. The best way to handle this is to understand the behavior and trend of those who churn so as to be always ahead of them. MTN Ghana, Kumasi was used as a case study to develop a predictive model for the prepaid telephony segment. The objectives of this study were to find out the extent of customer churn in MTN Ghana, Kumasi, the causes and effects of customer churn and to develop a predictive model for churn in the telecommunication industry. Questionnaires were used to find the causes of churn from the customer's perspective. An already defined churn variable dataset of 3333 records was used for the Predictive Model with Data Mining Techniques. The monthly churn rate for the industry is 2.5%. Poor network quality, high call charges, poor customer service and promotions from competitors are the major causes of churn. Even with the low churn rate the effects on the telecommunication firms are serious; Churn affects Market share, frustrates effort to achieve projected revenue, dissatisfied customers dent the brand image, increases operational costs as it requires marketing intervention to win-back churners as well as potential churners. Developing the predictive model, the neural network was used to calculate the propensity for a customer in the dataset to churn while the decision tree describes the behavior of the churners. The propensity for a customer to churn is 1.03 times, customer service calls, day call and international calls were the major characteristics exhibited by the churners.

TABLE OF CONTENT

Pages

LIST OF FIGURES:

LIST OF TABLES

CHAPTER ONE

INTRODUCTION

1.1. Background of the Study

The era where by firms just concentrate on adding to their customer base is thing of the past Customer retention has been very vital to all business of late. Any business with the aim of sustaining growth should not aim at only adding up to its customer but have a strategy of maintaining them. This will provide the avenue for cross-selling of products and services. To generate customer value, Freeman (1999) advocated that firms should try and keep their customers.

In this computer age where information is easily available, customers are more informed about better prices, products and services that suit their needs. (Perppard, 2000) the internet has given power to customer as they decide what firms should produce but not stick to what firms produce. Electronic Commerce has made competition more intense amongst firms, (Lejeune, 2001).is likely to increase the attrition rate of customers of a firm. To win this war firms should be able to understand their customer behaviuor so as to predict what they are likely to do in the near future so as to prevent them from switching to a competitor. (Geppert, 2002)

Churn" refers to the number of customers who, over a given time period, leave a Customer Service Provider. Customers lost to churn represent a major cost for Customer Service Providers, given the costs of acquiring new customers in a highly competitive market. Churn management systems attempt to identify customers who are likely to churn, and the value of such customers, based on data the service provider is able to obtain about them. Once identified, at-risk customers may be offered loyalty incentives based on the value of the customer to the carrier. (http://www.tmforum.org/ChurnManagement/7252/home.html)

According to Chorleywood Consultancy decreasing the churn rate by 1% will increase profit by 6%. (http://www.wirelesspedia.com/show/company/Chorleywood_Consulting/1305.html#)

With a sophisticated and well functioning churn management solution a firm can

- Retain the high value subscribers resulting in increased Average Revenue Per User
- Assure the most effective usage of the allocated resources for churn prevention due to well defined and good targeted offers
- Have maximal control in your hands by accurate and up-to-date reporting and evaluation.

To achieve this firm can:

- Amaze their mobile subscribers by demonstrating how much they understand their needs! Implement more customer centric and more targeted churn prevention business processes with much shorter reaction time.
- Additionally, due to the feedback and evaluation mobile telecommunication firms can continuously adapt churn management activity to the market circumstances.

- Technically, churn management should be moved from Business Intelligence domain to the everyday operation. To do so - and due to the limited headcount and budget constraint firms need a good system with high level of automation.

In the telecommunication market, competition is very high and the products and offerings are more and more comparable. This leads to reduced customer loyalty. Losing an existing high-volume customer means losing lots of revenue. It is more expensive to gain a new customer than to retain an existing one. Analyzing customer data and customer behavior is the basis for understanding the needs of your customers. It's necessary to identify customers that are willing to move to a competitor before they do so. (Ahn et al, 2006) As a conclusion firms have to make the right offering to the right customer at the right time. Churn Management helps to increase customer loyalty and to leverage existing customer assets. (Bolton et al, 2000)

"Churn costs European and U.S. telecommunications companies an estimated 4 billion dollars each year," said Jim Davis, SAS Institute's global IT strategist. "With annual churn rates of around 25 to 30 percent, it typically takes three years and costs up to $700 in Europe for a telecommunications company to replace each lost customer with a new one. Clearly, a solution that lets organizations reverse churn can contribute directly, and considerably, to a telco's ability to survive in today's deregulated and highly competitive telecommunications industry."

The table below annual churn rate for ten (10) well-know telecommunication firms in the world, presented by Inside Market Research.

Table 1.1.1 Churn Rate for some Telecommunication companies (Source: http://tinyurl.com/raqwv)

TELECOMMUNICATION COMPANY	**ANNUAL CHURN RATE %**	**YEAR**	**OPERATING COUNTRY**
Globe	31	2003	PHILPINES
U.S. Cellular	8	2005	USA
Virgin Mobile	14	2005	G.BRFITAIN
Nextel	16		USA
Vodaphone	17.2	2005	ITALY
Alltel	19	2005	USA
Hutchison Telecom	20	2005	INDIA
Cingular	23	2005	USA
Sprint	23	2005	USA
T-Mobile	34.8	2005	G.BRITAIN
Average Churn Rate	**20.6**		

1.2 Statement of the problem

Telecommunication firms spend a high percentage of their operation cost on try to win back customers who have left. With a high competitive nature of the telecommunication industry, firms should be more reactive than proactive when it comes to customer satisfaction. The drive to acquire more customers is the order of the day now, with retention strategies relegated to the bottom. The revenue a telecommunication firm generates from a new customer cannot much up to what an existing loyal customer will bring. MTN for example deletes subscribers who have been inactive for six months, recycle the number, spend money to package and resell. This cost could be prevented if there was a any mechanism to really understand what these customer expects and providing them with tailor made products and service to prevent them from switching. Customer churn has serious consequence to firms who do not have any retention strategy to avoid it; its frustrate projections in revenue, denting of company image, increased operational cost etc. Most customers churn partially by using other networks besides what they have already, under such situation market share will not fall but Average Revenue Per User falls thus affecting profit margins. To avoid these negative effects firms should always be ahead of customer's expectation by understanding their behavior so as to predict their next move.

1.3. Objectives:

1. To determine the extent of Customer Churn in MTN Ghana, Kumasi

2. To determine the causes of customer churn in MN Ghana, Kumasi.

3. To examine the effects of Customer Churn on MTN Ghana, Kumasi

4. To find out features that can be utilized in order to build a predictive model for customer churn in pre-paid mobile telephony industry.

1.4 Research Questions

1. What is the extent of Customer Churn in MTN Ghana, Kumasi?

2. What are the causes of customer churn in MTN Ghana, Kumasi?

3. What are the effects of Customer Churn on MTN Ghana, Kumasi?

3. What features can be used to build a predictive model for customer churn in pre-paid mobile telephony industry?

1.5 Significant of the Study

The significant of this study to me as a researcher is to understand why a customer will decide to change his service provider. To MTN, it will help the company to know what really cause it customers to churn to their competitors. MTN will also know the customers who are likely to churn and find ways of retaining them instead of wasting resources on customers who do not have any intention of leaving. To the academia this study will add up to the existing literature and also form basis for further study in other industries. Ghanaian companies who are only interested in customer acquisition to understand that customer do leave if they don't get what want and thus the need to develop the right strategy to retain their customers.

1.6 Scope

The study is Limited to MTN subscribers in Kumasi, both current and previous subscribers.

1.7 Brief Section on Methodology:

Methodology talks about framework for conducting the study. The population of the study is MTN subscribers (current and former subscribers) in Kumasi. A sample of 60 was used. The sampling technique used were random, snow balling and judgmental.

Both primary and secondary data were collected through questionnaires and analyzed with SPSS. Data mining models like the Tree Diagram was used to develop the model.

1.8 Research Limitations

The research, like all other researches, was not without its limitations. The follow are some of the limitations that we faced with during our research:

- One of the major limitations of this research was data classification and data confidentially in MTN that prevented the researcher to have access to a part of customer's data such as billing and credit data. This forced the researcher to calculate the monetary features manually and deprived us from involving the credit features into the model building
- Lack of demographic data of customers was also a limitation in conducting this research.

1.9 Organization of the Study

This thesis starts with an introduction of the study with the background into churn management. The statement of the problem under investigation, objectives, significance, scope and limitation to the study are presented in chapter one.

Literatures were reviewed the objectives in line with in chapter two. The concept of customer, what customer churn is all about, causes, effects and its managements were reviewed. The concept of data mining which was used to develop the model was reviewed together literature on Customer Relationship Management.

The methodology, which describes the procedures, tools and techniques used in this study are all presented in Chapter Three. Chapter four contains the analysed data. Answers to all the objectives are presented in this chapter with the summary of findings, conclusion and recommendation in Chapter five.

CHAPTER TWO

LITERATURE REVIEW

2.1 Concept of customer

The concept of consumer and for that matter customer has evolved through time. Philosophies about the consumer have changed through the production concept period to the societal marketing concept period (Kotler *et al*., 2002). The notion about the customer changed, owing to the understanding that the customer plays a crucial role in the organization. Before the 1960s the consumer was perceived to consume whatever was produced and therefore was not seen as a vital 'ingredient' in the production strategy. A vital factor in this change is the competition that organizations are facing due to globalization and the liberalization of the market. Besides, it has been noted that it is cheaper to retain existing customers than recruiting new customers (Donio, Massari and Passiante, 2006)

2.2 Customer Churn

According to Hadden *et al.* (2007), mobile telecommunication have become the dominant communication medium over the last two decades. In many countries, especially developed ones, the market has reached a degree of saturation where each new customer must be won over from the competitors. At the same time, public regulations and the standardization of mobile communication now allow customers to easily move from one carrier to another, resulting in a very fluid market.

Since the cost of winning a new customer is far greater than the cost of preserving an existing one, mobile carriers have been shifting considerable attention from customer acquisition to customer retention (Fildes, 2002). As a result, churn prediction has emerged as a crucial mobile Business Intelligence (BI) application that aims at identifying customers who are about to transfer their business to a competitor.

Song *et al*. (2007) emphasized that a good churn prediction system should not only pinpoint potential churners successfully, but further provide a sufficiently long horizon forecast in its predictions. Once a potential churner is identified, the retention department usually makes contact and, if the customer is established to be a churn risk, takes appropriate measures to preserve her business. Thus, a long forecast horizon is an obvious advantage since the further away the customer is from actually making the churn decision, the easier it is to prevent that decision at a significantly lower cost. Naturally, retention efforts are allocated limited resources and thus only a tiny fraction of the subscriber pool can be contacted at any given time.

The customer churn is closely related to the customer retention rate and loyalty. Hwang *et al.* (2004) defines the customer defection the hottest issue in highly competitive wireless telecom industry. They suggest that churn rate of a customer has strong impact to the long term value because it affects the length of service and the future revenue. Hwang *et al*. also defines the customer loyalty as the index that customers would like to stay with the company and indicated further that churn describes the number or percentage of regular customers who abandon relationship with service provider.

2.3 Causes of Churn

In an intensely competitive environment, customers receive numerous incentives to switch and encounter numerous disincentives to stay. Geppert (2002) gave the following as some of the causes churn;

Price: Particularly in the wireless and long-distance markets, carriers often offer pricing promotions, such as relatively low monthly fees, high-volume offerings (fixed number of minutes at a reasonable fee per month), and low rates per-minute. These price incentives can provide residential customers, in particular, with powerful incentives to change carriers.

Service quality: Lack of connection capabilities or quality in places where the customer requires service can cause customers to abandon their current carrier in favor of one with broader reach or a more robust network (Peppard and Rylander, 2006).

Fraud: Customers may attempt to "game the system" by generating high usage volumes and avoiding payment by constantly churning to the next competitor.

Lack of carrier responsiveness: Slow or no response to customer complaints is a sure path to a customer relations disaster. Broken promises, long hold times when the customer reports problems, and multiple complaints related to the same issue are sure to lead to customer churn.

Brand disloyalty (or loyalty to another): Brand issues may arise due to service or other issues experienced over time, mergers or acquisitions involving the incumbent carrier, or entry into the market of another carrier with strong brand recognition and reputation. Marginal brand loyalty can often be overcome by competitors' incentives.

Privacy concerns: Consumers have an increasing awareness that companies they deal with have a lot of information about them, including their spending habits, personal financial information, health information, and the like. Breaking of privacy promises, publicized privacy problems, telemarketing, and other issues are causing many customers to consider their personal privacy as an asset and they are holding their service providers responsible for keeping privacy promises.

Lack of features: Customers may switch carriers for features not provided by their current carrier. This might include the inability of a particular carrier to be the "one-stop shop" for all the customer's communications needs.

New technology or product introduced by competitors: New technologies— such as high-speed data or bundled high-value service offerings—create significant opportunities for carriers to entice competitors' customers to switch.

New competitors enter the market: The mere existence of viable competitors to the incumbent carrier may cause certain disloyal customers to churn. Further, as competitors enter new markets, they often offer short- or long-term incentives to new subscribers to build market share.

Billing or service disputes: Billing errors, incorrectly applied payments, and disputes about service disruptions can cause customers to switch carriers. Depending on the situations, such churn may be avoidable.

2.4 Effects of Customer Churn

Preventing customer churn is critical for the survival of mobile service providers because it is estimated that the cost of acquiring a new customer is about $300 or more if the advertising, marketing, and technical support etc are all taken into consideration. On the other hand, the cost of retaining a current customer is usually as low as the cost of a single customer retention call or a single mail solicitation (Berson *et al.* 2002). The high acquisition cost makes it imperative for mobile service providers to devise ways to predict the churn behavior and execute appropriate proactive actions before customers leave the company.

In addition to lost revenue, customer churn means increased activation and deactivation costs. In the global wireless industry, these amount to $10 billion per year, according to an August 2001 study by International Data Corporation (Geppert, 2002).

Geppert (2002) indicated that a high churn rate also puts pressure on companies to win new customers. The cost of acquiring each new customer ranges from $350 to $475 and providers need to retain these new customers for more than four years to break even. Replacing old customers with new ones carries other burdens. In addition to marketing and advertising, companies incur costs associated with provisioning new customers, as well as increased risks associated with billing issues and other revenue assurance matters. Customer churn also generates soft costs: loss of brand value when dissatisfied customers tell others about their experiences, lost opportunities for cross-selling of complementary products and services, and a potential domino effect with respect to the carrier's remaining customer base.

Further, the deactivation and disconnection of customers brings inherent risk of revenue and margin deterioration, particularly when multiple service providers are involved.

Finally, the potential impacts on profitability that come from inactive, underutilized, and otherwise unprofitable network facilities must be considered (Ahn *et al*., 2006).

2.5 Technological Centricity and the Notion of Churn Management

Churn prediction is a case in point in terms of the discussion on the efficiency of various tools and techniques of manipulating data. According to Hung *et al*. (2006), churn management is a framework of two analytical modelling processes. This they indicated as predicting "who" are about to churn and, second, coming up with the most effective way to react to the targeted customers. They indicated that Owczarczuk's (2010) study of data mining models for identifying "betrayers" among prepaid customers in the telecommunications industry is another example.

Baurdeau *et al.* (2005) indicated that technological innovation in the telecom industry is customer centric and emphasized that addressing customers' needs is an utmost priority. The problem of loyalty still remains one of the most vital problems. To address the current limitations of churn prediction technologies in terms of determining the right customers as well as on whom to spend retention and loyalty resources, the mobile carriers need to re-evaluate or redefine the notion of churn management.

2.6 Data Warehousing, Mining and Visualization

Bose and Chen (2009) indicated that the two main factors that affect the vitality of telecommunications are the rapid growth of modern technology and the market demand and its competition.

These two factors, according to Bose and Chen (2009) in return create new technologies and products, which open a series of options and offers to customers, in order to satisfy their needs and requirements. However, one crucial problem that commercial companies in general and telecommunication companies in particular suffer from is a loss of valuable customers to competitors. In a customer-centric marketplace, price, product, and even customer service are fluid by necessity. The carrier's ability to offer choice and respond to—or better yet, anticipate—needs of individual customers has become a major competitive advantage. For this reason, managing customer churn is largely a customer relationship management issue. Through effective customer relationship building and management, loyalty can be gained and many causes of churn mitigated.

The main problem with churn is that customers don't announce their intentions in advance (Kim and Yoon, 2004). It's up to the carrier to uncover evidence of potential churn, ideally even before the customer solidifies feelings or intentions. Ten years ago this would have been a nearly insurmountable challenge. Today, effective business processes enabled by technology can help reveal customer behavior patterns and aid in assessing the profitability of various customer segments, what is important to them, and how the carrier can build loyalty within the most valued customer sets (Baurdeau *et al.*, 2005).

Sohn and Kim (2008) emphasized that communications companies are sitting on perhaps the richest proprietary customer databases of any industry. Communications usage patterns and service histories reflect personal buying habits, and communications data is relatively easy to capture, store, retrieve, and analyze. To retain customers, carriers need to unlock the value hidden in these massive databases.The tools for performing such analyses of customers include data warehousing, data mining, and data visualization Han and Kamber, 2006).

While all carriers have proprietary customer information databases (albeit with varying degrees of accuracy, maintenance, and productive use), the warehousing and mining of the data can either be performed in-house with the requisite technology platform or outsourced to a telecom-focused CRM adviser. In fact, advances in CRM technology give carriers a choice among a wide range of software packages and customized solutions. In any case, ongoing analyses of real-time data enable a carrier to intervene with a range of customer retention options (Hwang *et al.*, 2004).

Data warehousing creates a central repository that consolidates all pertinent data from relevant systems and external sources in a consistent format to facilitate user access and modeling. By having all such data available simultaneously and uniformly, analysts can uncover relationships between customer characteristics, customer value, and churn likelihood (Ahn *et al*., 2006). Data warehousing provides the platform for data mining and data visualization.

According to Hung *et al.* (2006), data mining is the process of searching huge volumes of customer data to uncover patterns, relationships, and trends in customer activity. Data mining can help develop customer profiles and detect historical associations between certain profiles and the propensity to churn. Data mining tools are used to analyze many profile-related variables, including those related to demographics, seasonality, service periods, competing offers, and usage patterns including feature usage. Leading indicators of churn potential include late payments, numerous customer service calls, and declining use of services. In data mining, one can choose a high or low degree of granularity in defining variables. By grouping variables to characterize different types of customers, the analyst can define a customer segment. A particular variable may show up in more than one segment. It is essential that data mining results extend beyond obvious information(Li and Raun, 2007).

2.7 Data Mining Techniques

Coussement and Poel (2008) stated that there are mainly two types of data mining techniques that are used in practice: supervised learning and unsupervised learning. Supervised learning requires that the data set should contain target variables that represent the classes of data items or the behaviors that are going to be predicted. The most important decision in customer churn management is the separation of churners from non-churners. This is a task that is quite capably handled by supervised learning techniques. Decision tree models are very popular in prediction of churn. Wei and Chiu (2002) for example used different subsets of the whole data set to generate different decision tree models and combined the results of those single decision tree models using a weighted voting approach and generated a final classification decision for churn. They included customer characteristics as well as their contract information in their churn model.

Unsupervised learning techniques on the other hand do not require the data set to contain the target variable. Clustering is a type of unsupervised learning technique that can be used to explore data sets in order to discover the natural structure and unknown but valuable behavioral patterns of customers' hidden in it (Thomassey and Fiordaliso, 2006).

Mobile telecommunication companies have used data mining techniques to identify customers that are likely to churn. Since the main purpose of applying data mining techniques in this area is prediction, supervised learning techniques are popularly used. However, the use of unsupervised learning techniques for churn prediction is rather limited.

2.8 Data mining Steps

Şimşek Gürsoy (2010) indicated that the introduction of "competition" in the telecommunications industry has given rise to many issues and situations that are quite "uncommon", "unnatural" and maybe even "unimaginative" for a utility type industry. Originally vertically integrated, mobile carriers now have to carefully address the needs of millions of customers, understand their behaviour, predict their needs and design products and services that will at best address those needs. The competition becomes even more fierce with the penetration of mobile phone usage steadily reaching its peak, as attracting new customers becomes extremely difficult and losing existing customers very easy, although painful. Şimşek Gürsoy (2010) gave the following as the steps in data mining:

Business Understanding: This initial phase of data mining focuses on understanding the objectives of the project and requirements from a business perspective, and then converting this knowledge into a data mining problem definition, and a preliminary plan designed to achieve the objectives (Rud, 2001). Churn analysis uses the data period in which customers are still with company, and focuses on customer retention. Customer retention consists of identifying which customers are likely to churn, determining which customers should retain and developing strategies to retain profitable customers (Rust and Zahorik, 1993).

The main thing in retention process is identifying churn ratio which is a very meaningful and vital determination for many companies. Determination of churn ratio indicators is also very important. By using those indicators, firms can make prediction on future behavior of new customers and can develop new strategies much before customers start to think about churn. Thus, it is vital to build a very successful and accurate churn model during the retention studies (Şimşek Gürsoy, 2010).

Data Understanding: The data understanding phase starts with an initial data collection and proceeds with activities in order to get familiar with the data. Identifying data quality problems, discovering first insights into the data and detecting interesting subsets to form hypotheses from hidden information are activities of this step.

Data Preparation: The data preparation phase covers all activities to construct the final dataset from the initial raw data. Data preparation tasks are likely to be performed multiple times, and not in any prescribed order. Tasks include table, record, and attribute selection as well as transformation and elimination of data for modeling tools.

Modeling: In this phase, various modeling techniques are selected and applied, and their parameters are calibrated to optimal values. Typically, there are several techniques for the same data mining problem type. Since some techniques have specific requirements on the form of data, stepping back to the data preparation phase is often needed.

Evaluation: At this stage of a project you have build a model (or models) that appears to have high quality, from a data analysis perspective. Before proceeding to final deployment of the model, it is important to evaluate the model more thoroughly, review the steps executed to construct the model, and to be certain that it properly achieves the business objectives. A key objective is to determine whether there is some important business issue that has not been sufficiently considered (Peppard and Rylander, 2006). At the end of this phase, a decision on the use of the data mining results should be reached.

Deployment: The creation of the model is generally not the end of the project. Even if the purpose of the model is to increase knowledge of the data, the knowledge gained will need to be organized and presented in a way that the customer can use it. Depending on the requirements, the deployment phase can be either as simple as generating a report or as complex as implementing a repeatable data mining process. In many cases it will be the customer, not the data analyst, who will carry out the deployment steps. However, even if the analyst will not carry out the deployment effort, it is important for the customer to fully understand which actions will be needed to carry out in order to actually make use of the created models.

The results obtained in the study can be used in marketing activities of the company. When the company organizes campaigns for its products and services, firm can give priority to the subscribers who are more likely to churn, and can reduce the loss of customers.

2.9 Data Mining Techniques for Churn Prediction

a. Decision Tree

For describing sequence of interrelated decisions or predicting future data trends (Berry & Linoff, 2004; Chen, Hsu, & Chou, 2003; Kim, Song, Kim, & Kim, 2005), Decision Tree Model is used. This technique is able to classify specific entities into specific classes based on feature of entities (Buckinx, Moons, Van Den Poel, & Wets, 2004; Chen, Hsu, & Chou, 2003).

To divide up a large collection of records into successively smaller sets of records by applying a sequence (Lee & Siau, 2001) or as Berry and Linoff (2004) suggested the use of simple decision rules. According to Ngai, Xiu, & Chau, (2009), decision tree technique has been proven to be among the top three popular techniques of data mining in CRM

is used. The technique is capable of classifying specific entities into specific classes based on feature of entities (Buckinx, Moons, Van Den Poel, & Wets, 2004; Chen, Hsu, & Chou, 2003).

Tan, Steinbach, & Kumar (2006) described each tree to consists of three types of nodes:

- Root Node
- Internal Node
- Leaf or Terminal Node

A record enters the tree at the root node. The root node applies a test to determine which internal node the record will encounter next.

There are different algorithms for choosing the initial test, but the goal is always the same: To choose the test that best discriminates among the target classes. This process is repeated until the record arrives at a leaf node. All the records that end up at a given leaf of the tree are classified the same way, and each leaf node is assigned a class label (Tan, Steinbach, & Kumar, 2006; Berry & Linoff, 2004).

b. Neural Network

Neural Network has an interesting history in the annals of computer science. The original work on the functioning of neurons – biological neurons – took place in the 1930's and 1940's before digital computers really even existed. While earlier interest developed on the subject focused on understanding the anatomy of the brain, it turned out that the model provided inspiration for the field of artificial intelligence and would eventually provide a new approach to solving certain problems outside the realm of neurobiology (Rygeilski et al, 2002).

Neural networks became popular in the 1980's because of a convergence of several factors. First, computing power was readily available, especially in the business community were data was available. Second, analyst became more comfortable with Neural Networks by knowing that they were closely related to known statistical methods.

Third, there were relevant data hence since corporate operations had been automated. What is Artificial Neural Networks (Neural Nets) represent an attempt at a very basic level to imitate the type of nonlinear learning that occurs in the networks of neurons found in nature. Real neurons use dendrites to gather inputs from other neurons and combines the input information, generating a nonlinear response when some threshold is reached, which it sends to other neurons using the axon. Analogous to this is the way Artificial neural networks is structured to work.

Figure 2.9.1 Neural Network Structure

According to Shaw et al (2001) The inputs(xi) are collected from upstream neurons (or Dataset) and combined through a combination function such as summation, which is tehn input into a (usually nonlinear) activation function to produce an output response (y), which is then channeled downstream to other neurons.

What types of problems are appropriate for neural networks? One of the advantages of using neural networks is that they are quite robust with respect to noisy data. Because the network contains many nodes (artificial neurons), with weights assigned assigned to each connection, the network can learn to work around these uninformative (or even erroneous) examples in the dataset. However, unlike other algorithms like Decision trees which produce intuitive rules that are understandable to nonspecialists, neural networks are relatively opaque to human interpretation.

2.10 The Concept of Customer Retention

In the mobile telecom industry, customers are able to choose among multiple service providers and actively exercise their rights of switching from one service provider to another. In this fiercely competitive market, customers demand tailored products and better services at lower prices, while service providers constantly focus on acquisitions as their business goals. Given the fact that the telecom industry experiences an average of 25-30 percent annual churn rate and that it costs 5-10 times more to recruit a new customer than to retain an existing one, customer retention has now become even more important than customer acquisition (Geppert, 2002). For many incumbent operators, retaining high profitable customers is the number one business pain.

Peter Drucker (1973), once famously claimed that the sole purpose of a business was "to create a customer". However, keeping the customer has become regarded as equally, if not more important, since a 5 percent increase in customer retention generated an increase in customer net present value of between 25 per cent and 95 per cent across a wide range of business environments. While the precise definition and meaning of customer retention varies between industries and firms, Harris (2003) has defined customer retention as the continuous attempt to satisfy and keep current customers actively involved in conducting business. Kotler and Keller (2006) are however of the view that attracting and retaining customers has a connection with forming strong customer bonds and defined customer retention as the intent to develop stronger bonds with the customer.

Customer retention is increasingly being seen as an important managerial issue, especially in the context of a saturated market or lower growth of the number of new customers (Ahmad and Buttle, 2003). From the industrial marketing perspective, the way to retain customers is by forging multi-level bonds comprising financial, social and structural bonds.

2.11 Customer Behavioural Intentions

There is growing evidence that customer perception of service quality affects their behavioural intentions (Johnson and Sirikit, 2002). Certain customer behavioural responses provide a strong indication that they are bound to the organisation. For instance when customers show a preference for one organisation over others, or when they praise the organisation.

It has also been argued that service excellence enhances customers' inclination to buy again, to buy more, to buy other services, to become less price sensitive, and to tell others about their positive experiences (Bolton *et al.*, 2000). Boulding *et al.* (1993) stated that service quality has a positive impact on customer's repurchase intentions and intentions to recommend the company to others. Zeithaml and Bitner (2000) on the other hand indicated that service quality influences different intentions, such as giving recommendations, doing more business, and willingness to pay more.

2.12 Data Mining and its Effects on Customer Retention

The outcome of applying data mining supports predictions of those customers most likely to churn and, possibly, when and why. These models help identify intervention strategies that can reduce churn among particular customer segments. They may also provide insight into ways to solve more fundamental root causes of churn, such as pricing, poor customer service, or service quality. When coupled with predictions of lifetime value by customer segment, it can support focused retention efforts. Moreover, they can be used to estimate the return on investment (ROI) of each retention effort as a basis for selecting among competing efforts. For service organizations to meet the service quality needs of their customers, they must understand their expectations of the service to their perception of the service actually received as propounded by Parasuraman *et al.* (1994).

In short, data mining's predictive capabilities paves the way for informed marketing strategies and real-time customer-retention strategies— from promotions and mailings to direct customer contact and new service plans (Geppert, 2002). Therefore mobile telecom companies can optimize their marketing intervention resources to prevent as many customers as possible from churning. In other words, if the telecom companies know which customers are at high risk of churn and when they will churn, they are able to design customized customer communication and treatment programs in a timely efficient manner.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

The research design is a framework for conducting marketing research (Malhotra, 2007). Thus it's the basic plan for conducting data collection and analysis phase. In the current chapter firstly the design of the research will be explained and scrutinized and afterwards the process of executing the designed research will be illustrated and explained.

3.2 Research Instruments:

This refers to the methods used in conducting the study. The time frame of the study was from October 2010 to March, 2011. Monthly churn rate for these months were used to determine the extent of customer churn in MTN. The customer's perception about causes of churn was gathered through questionnaires which was analysed with SPSS. The Manager responsible for churn management was interviewed to get the effects of churn on MTN. To develop the predictive model an already defined churn dataset with 3333 records of 20 fields from October 2010 to March 2011 were made available by MTN. Data mining Techniques were used to develop the model with SSPSS Clementine, the Neural Network data mining technique was used to derive the propensity for a customer in the dataset to churn where as the Decision Tree showed the characteristics of those who churned.

3.3 Population:

This is the entire group of persons with characteristics which will be of interest to the study. Thus population will include all MTN users and former users in Kumasi. About

20% of the 9 million MTN subscribers are in Kumasi, according to the Marketing and IT Divisions of MTN. Thus the population size for the study was 1.8 million subscribers.

3.4 Sampling/sampling Techniques:

Due to the large population size together with cost and time constraints a sample which is a percentage of the population is selected to represent the bigger population. The sampling techniques show how the sample will be selected. A sample of 56 respondents was selected to represent the population to find out what will cause them to churn. Since all respondents have an equal chance of being selected the random sampling technique was used. However since those who have already churned are very important in finding the causes, snow ball was used. The 3333 records used to develop the predictive model' provided by the IT Department was randomly selected from subscribers in Kumasi. Two staffs at the Marketing Division, MTN, the supervisor and one research staff were contacted to find out how the company is affected by customer churn and how it is being managed.

3.5 Data Collection:

This is the way information is collected from the sample. Both primary and secondary data was collected for this study. The primary data was gathered through close ended questionnaires to find out if customers will churn base on; a) Network Quality, b) Customer Care or c) Cost or affordability. Open ended questions were also asked to capture other causes rather than those specified.

Secondary data was collected from monthly Customer satisfaction Index CSI) figures for all networks from national Communication Authority (NCA). CSI figures for Network

Quality, Customer care and Cost was collected. Internal secondary data were collected from MTN database to help in the churn prediction model which uses data mining.

3.6 Churn Predictive Model:

Data Mining was used to predict whether a particular customer churned over a given period of time and also to understand why customers churned or stayed.

3.6.1 Data Selection

MTN made available a dataset named churn which had already a churn variable for current churned customers. The dataset contained 3,333 records of both churned and active customers and 20 different fields on the customers. The data was divided into 50% training and 50% validation.

3.6.2 Data Pre-processing

The data pre-processing stage consists of

1. Describing the dataset
2. Removing statistically insignificant fields
3. Define and introduce the target field
4. Exploratory analysis with respect to the target variable

3.7 Data Analysis:

This is the way by which data collected from the field is put together in a meaningful manner for easy comprehension. The primary data was analysed with SPSS and the Data Mining, SPSS Clementine.

3.8 Data Presentation:

This is how the anaysed data is presented for easy understanding and help in understanding trends or relationships between variables. The data in this study was presented in tables, bar charts and graphs and some aspect of narrative form.

3.9 Background of MTN Kumasi.

MTN, Ghana is a Multi-National Telecommunication company operating in 21 countries. MTN Ghana have three Business Units with Kumasi being part of the Northern Business Unit. The core business of MTN is the provision of communication service, both voice and data. MTN Ghana metamorphosed from the analog to GSM to GPRS then to EDGE network. Currently the company run on 3.5 G (3^{rd} Generation) network and was the first to introduce the technology in the country. MTN is the number one telecommunication company in Ghana with about 53% market share according NCA.

MTN Ghana provides both postpaid and prepaid service to suit the different segments of the market. This study focuses on the prepaid segment of the market. The company has different call and data plans to suit different customer needs. MTN has more products and service than any other mobile network in the country. Services ranging from, voice mail, voice sms, collect call, smart clip, conference call among others. Due to the intense competition in the industry, the company now sells customized and subsidized items like Modems, smart phones, laptops and low end handsets to provide one-stop communication facility for customers. Deviating from its core business, MTN now operate Mobile Money which gives customers the chance to receive and transfer money via the mobile phones and recently launched insurance service. These services are geared towards customer.

MTN as other company is faced with customer churn due to the competitive nature of the industry and the impending Mobile Number Portability which allow customer to maintain their numbers on another networks.

MTN has about 6 service centres to provide customer service and serves as sales points for customers. Besides these service centres are the 24 hour call centre and connects stores established in areas where service centres are not available. These are all put in place to make sure customers get access to our products and services and also to have their problems resolved.

MTN as any other company have to deal with the problem of customer churn in the mist of stiff competition\

‘

CHAPTER FOUR

DATA PRESENTATION, ANAYSIS AND DISCUSSION

4.1 Introduction

In this chapter the research questions are answered by analyzing data collected from both primary and secondary sources. Data on the extent of customer churn, causes and effects of customer churn were analysed with SPSS and presented in tables. The main objective of building a predictive

4.2 Extent of Customer Churn in MTN:

MTN marketing Division uses its Oracle software to determine the monthly churners or potential churners. Customers who lines have not been active for the past 20 days are considered as a churner or a potential one. These customers have not received or made calls or SMS and GPRS on their line during the period under review.

Table 4.2.1 below shows the monthly churn rate as a percentage of MTN subscribers from October 2010 to march, 2011 provided by the Research Department of the Marketing Division

Table 4.2.1: Monthly churn rate (%) of MTN subscribers

(Source: Research Department, Marketing Division, MTN, Ghana)

MONTH	**CHURN (%)**
OCTOBER	2
NOVEMBER	2.5
DECEMBER	3
JANUARY	2.7
FABRUARY	2.4
MARCH	2.1
AVERAGE	**2.45**

From the table the average monthly churn rate at MTN from October , 2010 to March, 2011 was 2.45%. This means for every month 2.45% of MTN subscribers either leave or are likely to churn to other networks. This monthly average falls within the yearly average of between 2-3 %.

4.3 Causes of Customer Churn in MTN

56 respondents were contacted to find out what will cause them churn from MTN. Approximately 90% of the respondents used MTN with only six(6) out of the 56 respondents not MTN subscribers, Table 4.3.1 Appendix two. 5 out of the 6 respondents who were not using MTN had used MTN before but stopped whilst the other one had never used MTN.

Table 4.3.2: Why respondent stop Using MTN

		Frequency	Percent
Valid	Poor Network Quality	30	53.6
	Bad Customer Care	7	12.5
	Promotions of Competitors	11	19.6
	Others	3	5.4
	Total	51	91.1

Asked what will make respondents stop using the service, 58.8% chose poor network quality 21.6% chose promotions of other competitors whilst 13.7% chose bad customer service.

It was realized that from Table 4.3.3, Appendix Two, 66% of the 50 active subscribers have churned partially as they use other networks beside MTN. Several reasons were attributed to this partial churn; from Table 4.3.2 the major causes are high cost and affordability, poor network and to enjoy promotions from competitors. Factors like poor customer service rendered to the by MTN, low cost and bonus airtimes provided by other networks.

Table 4.3.4: **Why do respondent use other network**

		Frequency	Percent
valid		18	32.1
	More Transparent	1	1.8
	Because Of Special Call	1	1.8
	Better Network and Low Cost	1	1.8
	Convenience	1	1.8
	Cost	11	19.6
	Cost and an Excellent Customer Care	1	1.8
	Less Cost and Good Quality Network	1	1.8
	Network Quality And Bonus	1	1.8
	Network Quality and Customer Care	1	1.8
	Network Quality And Very Affordable	1	1.8
	Poor Network Quality	10	17.9
	Promotions(Bonus)	6	10.7
	Quality Customer Care	2	3.6
	Total	56	100.0

Asked further why they use other networks, 26.4% attributed it to cost, that is MTN is perceived as costly compared to the other networks. 27% attributed it to the poor network quality of MTN with 10% being lured by the promotions of their other service providers unlike MTN, 7.2% attributed it to poor customer service, the rest see MTN not to transparent and more inconvenient for them.

This shows that customers leave when they are not satisfied with service rendered. Poor network which cause call drops, calls not going through, poor voice quality are features associated with poor network. Customer service is also very vital and when bad causes customer to churn, customers finding it difficult to get to the call center and have their problems solved and having to wait for longtime at the service centre before being attended to frustrate customers and force them to leave. Cost also came up strongly as a cause. Even though cost is not to high, competitors have call charges are lower than MTN and have more promotion running attracting subscribers of MTN either to churn entirely or partially.

4.4 Effects of Customer Churn on MTN.

Customer churn ie loosing your customer to your competitors is one aspect business try to prevent because of the negative effects. With the world being global with information readily available, customer always search for better alternatives. With the intense competition in the Telecommunication industry, losing a customer to competitor is a big customer to MTN.

An interview with the Head of Churn Management Department of Marketing Division of MTN, Ghana, revealed that customer churn has a negative impact on market share. With fierce competition in the industry losing in market share is disastrous for MTN. Even with the current market of 53% as at March, 2011, MTNs market share have been falling and is expected to fall further with the entry of new companies like Glo.

Customer churn frustrates MTN effort to achieve projected thus making forecast in revenue difficult. Throughout the phases of partial to actual churn the revenue generated falls throughout as no customer do not use the service.

Dissatisfied customers also dent the company's image. The image of every company is very vital to the success of the company. Once the image is dented MTN does not only suffer from customer retention but acquisition as well as no customer will want to do business with a bad image.

There is also the problem of increases operational costs as it requires marketing intervention to win-back churners as well as potential churners. About 1.5% of MTN total expenditure for the year is spent on churn management. This percentage is expected to increase as competition in the industry heightens.

4.5 Churn Predictive Model

4.5.1 Description of the Churn Data set

MTN submitted a text file called churn with size 432kb form its database that has 20 fields for 3,333 customers.

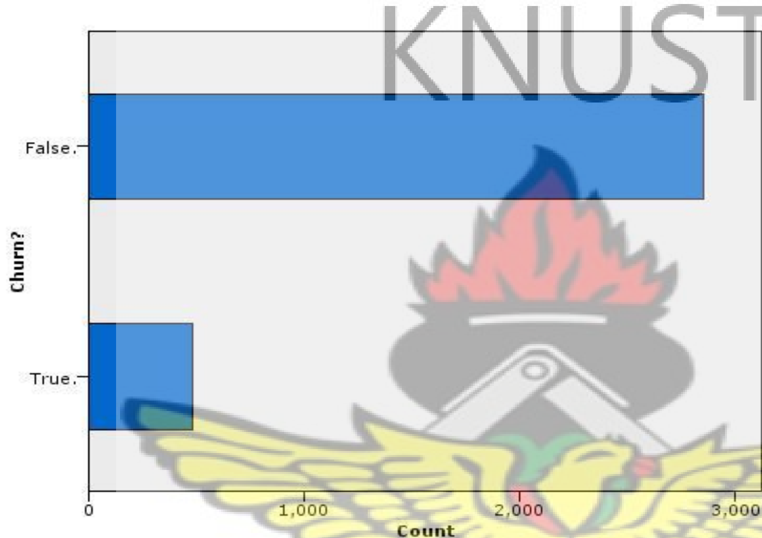
The Table 4.5.1 in (Appendix Two) shows the Description of variables from the dataset from MTN's database.

4.5.2 Churn Variable

In the dataset the variable churn has already been defined. Customers whose lines had been inactive for 20 days were tagged as churned. 87 customers representing 2.6% of the 3,333 customers in the dataset have churned.

The figure below show false and true churn of the dataset.

Figure 4.5.1: Churners and Non Churners



4.5.3 Exploratory Analysis

1. **Correlated Variables**

From the results generated by SPSS Clementine, Day charge, Eve Charge, Night Charge, Intl charge are perfectly correlated with Day Minutes, Eve Minutes, Night Minutes and Intl Minutes respectively. This confirms the fact that Charge of calls is a function of the minutes. Since the charge aspect is a function of the minutes we will take out the charge variables from the model. Table 4.5.2 in the appendix two shows the descriptive statistics and the various correlations strengths of the variables amongst all variables. There are no other correlated variables among the variables.

Comparing the differences in means of the fields with respect to the churn variable to understand whether the differences are significant or not in which case the variable can be flagged as a possible causal field for churn. Table 4.5.2 in appendix two generated with SPSS clementine flags, No. of Voicemail messages, Day Minutes, Evening minutes, Night minutes, international minutes and international calls as important variables. That is, these variables have significant differences in mean among churned and active customers. They can be probable reasons for churn.

4.5.4 Histogram with Churn overlay

The figures 4.5.3 to 4.5.14 in appendix three show how the variables are related to churn generated by SPSS Clementine.

Account length, Number of day calls, Night Minutes, Night calls, Intl Minutes from figure does not show any obvious relationship with churn.

However, from the histogram, churn numbers increase with increasing day minutes and evening minutes increase. Churn numbers are also prevalent in customers with those who have subscribed to international call plans and those without the voicemail plan.

4.5.5 Modeling:

In this phase, various modeling techniques are selected and applied and the parameters calibrated to optimal value .For this study, since the dependent variable has two outcomes and all the variables can be normalized, Neural Networks is applied to train our dataset. Subsequently decision tree is used to draw the conclusions in our model.

Based on the distribution 14.5% of subscribers churn whilst the remaining 85.5% maintain their subscription to the service. If the data set is analyzed and modeled using these ratios, outcomes will be biased. In order to have an unbiased result, the distribution should be balanced. A balance node is created on SPSS Clementine to boost the number of churners so that our dataset records 50% churners and 50% non churners as shown in the figure below.

Figure 4.5.15.: Boosted distribution of Churners and Non Churners

Since we are using Neural Networks to train our dataset, all inputs have to be normalised. Therefore all inputs are standardized with the minimum – maximum normalisation criterion. The formula used is $X = \frac{X-Min(x)}{range\ (x)}$ where X is the variable in question.

Now our data is ready for modeling. The dataset is divided into 50% training set and 50% testing set. The Neural Network model is built on the training set with SPSS Clementine.

At this stage the Neural Network model is used in Clementine to train our data to determine the variables that are important in predicting churn or retention. One of the advantages of using Neural Network is that they are quite robust when there are a lot of irregularities in the data and so working on although an abstract from the company's dataset which might have been refined, the model is still trained with Neural Network. The variable importance as detected by the Neural Network Model is shown in the figure below.

Since the degree of importance of Evening Calls, Account Length, Number of Voicemail Messages Night calls and International Calls are less significant from our neural network model on the training set, they shall be omitted and the model run again. The result of the omitted variables is shown in the figure 4.5.16 in appendix three.

A Classification and Regression decision Tree Model is built on the Training Set. The accuracy of these two models predicting churn on the training set is shown below.

Table 4.5.3 Neural Network Predictions Against Actual Churn from Training Set

Correct	2581	90.37%
Wrong	275	9.63%
Total	2856	

Table 4.5.4 CRT decision tree Model's prediction accuracy of Churn against actuals from the training set

Correct	2358	82.56%
Wrong	498	17.44%
Total	2856	

From the above table our Neural Network model is able to predict with an accuracy of 90.37% on the Training set whilst the Decision tree Models prediction accuracy is 82.56%.

To test our model, the model is applied on the Testing Set partition and measure the accuracy. This time the Neural Network Model's accuracy in predicting churn is 83.54% which means that our model is overtrained at the training partition compared to the testing partition by nearly 7%. The decision tree however gives an accuracy percentage of 80.71% with an overtraining percentage of nearly 2%.

Table 4.5.5. Neural Network Predictions Against Actual Churn from Testing Set

Correct	2416	83.54%
Wrong	476	16.46%
Total	2892	

Table 4.5.6 CRT decision tree Model's prediction accuracy of Churn against actuals from the testing set

Correct	2334	80.71%
Wrong	558	19.29%
Total	2856	

.

The decision tree model unlike the Neural Network model is able to give a set of rules to bring out the determinants of churn. So whilst the Neural Network was used to find the customers with the highest propensity to churn for target marketing, the decision tree model finds out the behaviour of those who churn and those who remain loyal.

4.5.6 The Decision Tree Model

NormCustSerCalls <= 0.389 [Mode: 1]

NormDmin <= 0.663 [Mode: 1]

NormIntlPlan in [0.000] [Mode: 1] => 1.0

NormIntlPlan in [1.000] [Mode: 0] => 0.0

NormDmin > 0.663 [Mode: 0] => 0.0

NormCustSerCalls > 0.389 [Mode: 0] => 0.0

The decision tree model chooses Customer Service Calls as the most important variable or determinant of Churn.

Rule 1: Customers who make more than 4 calls (>0.389 denormalized) to the call center are more likely to churn**.** 88% of customers who make more than 4 calls to the Service center are likely to churn. Concentrating on this Rule, a subscriber is 1.76 times as likely to hit on a churner as by using random selection on the entire data. This is shown '[; Gains Table for Churners in appendix two

Rule2: Customers who make less than 4 calls but have Minutes of calls during the day greater than 232.58(denormalized) are morel ikely to churn. 75.98% of customers who make less than 4 calls to the Service center but record more than 232.58 minutes of day calls within the day churn. In analyzing this for action we do not forget that day calls perfectly correlates with day charges and these day charges are what the company recognizes as peak hour charges.

Concentrating on this Rule, a subscriber is 1.52 times as likely to hit on a churner as by using random selection on the entire data. This is shown in the Gains Table for Churners in appendix two

Rule 3: Customers who make less than 4 calls but have minutes of day calls less than 232.58 minutes and make international calls are more likely to churn 77.98% of customers who make less than 4 calls to the service center but record minutes of day calls less than 232.58 minutes and make international calls churned. Concentrating on this Rule, subscriber is 1.55 times as likely to hit on a churner as by using random selection on the entire data. This is shown in the Gains Table for Churners.

4.5.7 Applying the Model:

Since our Neural Network Model provides a slightly better accuracy in predicting churn than the Decision tree model we use it to calculate the propensity to churn for our datasets to know which people to target for marketing.

The lift chart, which measures the percentage of churners in every quantile(demacation into 10 equal parts in decending order) compared to the percentage of churners in the overall dataset, for our neural Network indicates that targeting the top 47% of customers based on their predicted probability to churn we are 1.77 times as likely to find a churner than using simple random selection for the entire dataset.

After the model has been built and accepted identifying the right offer for every target group is left for the marketing experts to decide and their impact will be assessed through our datamining process again.

CHAPTER FIVE

SUMMARY OF FINDINGS, CONCLUSION AND RECOMMENDATION

5.1 Introduction

This chapter puts together all the information gathered from the first four chapters. The objectives, literature reviewed, the methodology and the data analyzed in the previous chapters.

The summary of findings generated out of the objectives is also presented in this chapter. A conclusion to the project as well as recommendation for further studies and to MTN as a company is presented in this chapter.

5.2 MTN Current Churn Management

MTN as at the time of study did not have any model to predict customer churn. Feature used to predict churn in MTN includes; Automatic Predictive Churn tool, which was used to alert marketing the number of subscribers who have not made any revenue generated activity for the past say 10, 15, 25, 30 45, 60 …days and engage them with value delivery offers to entice them to make any revenue generated activity.

To know the actual number of subscribers, any subscriber whose line has not generated any revenue for six months is deleted and recycled. MTN believes these subscribers are true churners. But not all subscribers in this group are true churners.

It was realized that about 30% of subscribers whose lines are deleted came back for their number but could not have them back since those lines have been recycled; these subscribers are false to churn. The reasons given for not using the lines were that some travelled outside. Others too did not know that lost line could be replaced or where to have it replaced. Some customers use other networks and as such stop using MTN, these customer later on decides to come back to MTN. others too were forced to churn because of MTN's process and procedures.

5.2 Summary of Findings

5.2.1 The Extent of Customer Churn at MTN

From the data analysed it was found that the average churn monthly churn rate for MTN was between 2 to 3 percent. Though this figure is small the actual number of subscriber who churns is rising. Since this is a percentage it might be deceptive if addition-on are not considered.

5.2.2 Causes of Customer churn

From the study it was realized the causes of churn amongst the respondents were poor quality network, bad customer service high cost of calls, and promotion from other networks. More than half of the respondents stated that they will churn due to poor network quality, high cost, and bad customer service. Because of these most of the respondents use other networks besides MTN to make up for lapses from MTN. Some even said they use MTN because most people are using in and because of their business they have to maintain their number.

5.2.3 Effects of Customer Churn on MTN.

The churn of customers have serious consequences on MTN. Churn affects MTN's Market share, frustrates effort to achieve projected revenue, dissatisfied customers dent the brand image, increases operational costs as it requires marketing intervention to win-back churners as well as potential churners.

5.2.4 Building a Predictive Model for Customer Churn

From the model it was realized that number of calls made to the customer service (ie Call Center) was the main determinant of churn. Customers call the call centre when they have problems or want to activate a service. Those made more than four calls to the call centre churned. This meant they had more problems and that MTN services were not easily available or technical.

Those customers who made less than four calls to the call centre but made more than 233 minutes of calls a day churned. Since call charge per second the minutes goes with cost. This means cost is very vital and those who talk more pay more. Most of those in this category make more business calls and as such increase their cost which affects their profit. Since they might not be able to reduce their minute call, the only option left is to find a cheaper alternative. The results also showed that those making international calls are all likely to churn. This is related to business and the fact that there are different zonal charges due to different international gateways. Most of those who made calls to the Zone 5 mostly Asian countries churned.

Concentrating on the Rules, on the average, a subscriber is 1.03 times as likely to hit on a churner as by using random selection on the entire data. The finding of this research has important application for companies that are active in mobile telecommunications market (especially the pre-paid ones).

Managing the great deal of data produced by customers in companies and organizations, can provide them with precious knowledge regarding their customers which can be exploited in developing new products, conducting retention campaigns, and also in across selling and up-selling the products and services of a company. This demonstrates the significance of applications of data mining in marketing. In fact mining the raw data produced by customers in their touch points with company can provide the company with a better insight toward their customers which helps them to conduct more efficient and also more effective marketing investments.

5.3 Conclusion

The problem that MTN was dealing with was to recognize the customers with high probability of churn in close future and target them with incentives in order to convince them to stay, but due to the absence of an accurate model for monitoring their clients' behaviour, the company was unable to distinguish the churners from non-churners. In such case, the company had two ways; whether to send all customers the incentives, which was clearly the waste of money or to quit the churn management program and focus on acquisition which is considerably more costly than the retention approach.

Under such circumstances the company decided to find a way in order to distinguish the churners from non-churners. This will help MTN to know the right people to target with their incentives. In this case, not only the model helps the company to distinguish the real churners, but also it prevents the waste of money due to the mass marketing.

Studying customer behavior with respect to churn is highly complex since customer behavior cannot be predicted with just a crystal ball. As a result amongst the various data mining techniques that can be used to predict churn, we choose Neural Networks model to train our data and calculate the propensity for every customer in our dataset to churn. Neural Networks is used because of how it is able to train our data to achieve comparatively high accuracy level. Decision tree model is able applied on our final neural model to interpret and give us the likely causative factors of churn.

The Cross Industry Data Mining Approach (CRISP-DM) was used to build the model. First the problem at hand was defined in terms of it business objectives and then an exploratory analysis of the data was done to find out insignificant variables and correlated variables.

The rules generated by the decision tree model were used to explain customer churn, whilst the propensity to churn scores generated by the neural networks model is used to establish the probability of a customer churning. A lift chart is generated from the neural networks model to determine which category or quartile of customers with high propensity to churn, if targeted will yield a much desired return or response.

Consequently the developed models are considerably able to distinguish the churners form non-churners and help the MTN to conduct a more efficient retention campaign. In fact by utilizing this approach the Company would be able to reduce the marketing cost and churns rate simultaneously.

5.4 Recommendation

It's recommended that MTN builds a predictive model for churn to help in their churn management. The company waste money pursuing mass churn management neglecting that fact that prospective churners portray certain behaviours which when realized will help in developing a better retention strategy. The market share is still high but revenue generated by a subscriber is reducing as they spend on the other networks. These customer are potential churners and as such strategies should be developed to encourage them to use MTN and at the same time working the network quality, customer care, cost and give free-bies to entice them.

More products and services that supports retention of customers such as; mobile money, mobile money insurance, phone number back up should be introduced. More corporate social responsibility programers such as the 21 Days Yello Care should be encourage so as to diffuse the notion the the company is just ripping of customer to amass profit for itself.

Competition in this industry is the fiercest in the country and if MTN should pursue acquisition without strategizing to retain them will be disastrous in the near future. Government policies such as the Subscriber Registration which require all subscribers to have their numbers registered will cause MTN to Lose customers. A more serious policy is the Mobile Number Portability which allows subscribers to maintain their number on another network. If MTN do not manage it churn properly will lose out as more will churn to other networks and still maintain their MTN numbers

Further studies should use the other data mining models besides Neural Networks and Decision Tree to find out if they will give a more accurate churn prediction than what was used. Further study on the postpaid to find out if they provide a high propensity to churn than the prepaid ror vice versa.

0REFERENCES

Ahmad, R. and F. Buttle (2003), "Customer Retention Management: A Reflection of Theory and Practice", *Journal of Marketing Intelligence and Planning,* Vol.20, No. 3, pp. 149-161.

Ahn, J., Han, S. and Lee, Y. (2006) Customer churn analysis: Churn determinants and mediation effects of partial defection in the Korean mobile telecommunications service industry, *Telecommunications Policy*, 30(10-11) pp.552–568

Bateson, J.E.G. and Hoffman, K.D. (1999), *Managing Services Marketing: Text and Readings*, 4th ed., Dryden Press, Orlando, FL,

Baurdeau, A., Liebenau, J. and Savin, B. (2005), A New View of Scale and Scope In The Telecommunications Industry; Implications For Competition And Innovation, *International Journal of Digital Economics*. 60(4) Pp.85-103.

Berson, A., Smith S and Thearling K (2002), *Building Data Mining Applications for CRM,* McGrawHill, New York

Bligh, P. and Turk, D. (2004), CRM Unplugged: Releasing CRM's Strategic Value, John

Bolton, R.N., P.K. Kannan, M.D. Bramlett (2000), "Implications of Loyalty Program Membership and Service Experiences for Customer Retention and Value", *Journal of the Academy of Marketing Science,* Vol. 28 No. January, pp.95-108

Bose, I. and Chen, X. (2009), Exploring business opportunities from mobile services data of customers: An inter-cluster analysis approach, *Electronic Commerce Research and Applications*, 9(3) pp.197-208

Boulding, W., A. Kalra, R. Staelin and V.A. Zeithaml (1993), "A Dynamic Process Model of Service Quality: From Expectations to Behavioral Intentions", *Journal of Marketing Research*, Vol.30, February, pp.7-27.

Brown, L., (2007), "What your customers really want: 7 Qualities of Customer Care", *Journal of American Salesman*, Vol. 52, Issue 5, pp. 12-15.

Chow, S and Holden, R. (1997), Toward an Understanding of Loyalty: the Moderating Role of Trust, *Journal of Managerial Issues*, Vol. 9, No. 3 pp. 275-298

Coussement K and Van den Poel D (2008), "Churn prediction in subscription services: An application of support vector machines while comparing two parameter-selection techniques," *Expert Systems with Application*, Vol. 34, no. 1, pp. 313-327

DeSouza, G. (1992), "Designing a Customer Retention Plan", *Journal of Business Strategy*, pp24-25.

Donio, J., P. Massari, and G. Passiante, (2006) "Customer Satisfaction and Loyalty in a Digital Environment: An Empirical Test," *Journal of Consumer Marketing*, 23(7), 445-457.

Drucker, P. F. (1973), Management: Tasks, Responsibilities, Practices, Harper and Row, New York.

Edwards, J. (2007), Get It Together with Collaborative CRM, *Inside CRM*. 2007-11-29 Tippit

Etzel, Walker, and Stanton (2004), Marketing, 13th Ed., Tata McGraw Hill, New Delhi

Fildes, R. (2002), Telecommunications demand - A review, *International Journal of Forecasting*, Vol. 18, Pp. 489-522.

Gefen, D. (2002), Customer loyalty in e-commerce, *Journal of Association for Information Systems,* (3), 27–51

Geppert, C. (2002), Customer Churn Management: Retaining High-Margin Customers with Customer Relationship Management Techniques, KPMG & Associates

Ghauri, P. (1999), in Ghauri, P. (Eds), Advances in International Marketing and Purchasing: From Mass Marketing to Relationships and Networks, JAI Press, Greenwich, CT.

Grönroos, C. (2000), Service Management and Marketing: A Customer Relationship Management Approach, Wiley, New York, NY.

Hadden, J., Tiwari, A, Roy, R. and Ruta D (2007), Computer assisted customer churn management: State-of-the- art and future trends, *Computers and Operations Research*, Vol. 34(10) Pp. 2902- 2917

Harris, L., L. O'Malley, M. Patterson (2003), “Professional Interaction: Exploring The Concept of Attraction”, *Marketing Theory*, Vol. 3 No.1, pp.9-36.

Hung, S., Yen, D. and Wang, H. (2006), Applying data mining to telecom churn management, *Expert Systems with Applications*, 31(3) pp.515-524

Hutt, Michael D. and Thomas W. Speh (2004), *Business Marketing Management: A Strategic View of Industrial and Organizational Markets*, 8th ed., Mason, OH: South-Western.

Hwang H., Jung T. and Suh E. (2004), “An LTV model and customer segmentation based on customer value: A case study on the wireless telecommunication industry”, *Expert Systems with Applications* 26 (2004) 181188.

Johnson, W. C. and A. Sirikit (2002), “Service Quality in the Thai Telecommunication Industry: A Tool for Achieving a Sustainable Competitive Advantage”, *Mgt. Decision,* Vol.40, No. 7.

Kobsa, A. (2002) “Personalized hypermedia and international privacy”,communucations of the ACM, Vol.45 pp64-7

Kotler, P. (2007), *Marketing Management – Analysis, Planning, Implementation, and Control*, 9th ed., Prentice-Hall International, Englewood Cliffs, NJ

Kotler, P. and K.L. Keller (2006), *Marketing Management,* 12th Ed., Prentice Hall, Pearson

Kotler *et al*. (2002), "Understanding the relationships among brands, customers and resellers," *Journal of the Academy of Marketing Science*, Vol. 28, No. 1, pp. 17-23.

Lawson-Body, A. and Limayem, M. (2001), “Business-to-Business Electronic Commerce: Impact of web site characteristics on Relationship Marketing Efficiency”, *Revue des Sciences de Gestion*, No. 5-6, pp. 113-158.

Lejeune, M. A. (2001). Measuring the impact of data mining on churn management. Internet Research: Electronic Networking Applications and Policy , 11 (5), 375-387

Li, T. & Ruan, D. (2007). An extended process model of knowledge discovery in databases. Journal of Enterprise Information Management. 20 (2), 169-177

Ngai, E., Xiu, L., & Chau, D. (2009), "Application of data mining techniques in customer relationship management: A literature review and classification", *Expert Systems with Applications*, 36, 2592-2602.

Owczarczuk, M. (2010), Churn models for prepaid customers in the cellular telecommunication industry using large data marts, *Expert Systems with Applications*, 37(6) pp.4710-4712.

Parasuraman, A., V.A. Zeithaml and L.L. Berry (1994), "Reassessment of Expectations as a Comparison Standard in Measuring Service Quality: Implications for future research", *Journal of Marketing*, Vol.58, pp.111-124.

Payne, A. (1994), Relationship marketing making the customer count, *Managing Service Quality*, 4(6), 29–31.

Peppard, J. and Rylander, A. (2006), From Value Chain to Value Network: Insights for Mobile Operators. *European Management Journal*, 24(2-3) pp.128-141.

Perreault, W.D. Jr., McCarthy,E.J. (2002), Basic Marketing, McGraw-Hill/Irwin, Boston

Reichheld, F.F. (1996), The Loyalty Effect; The Hidden Force Behind Growth, Profits and Lasting Value, Harvard Business School Press, Boston MA.

Reinartz, W.J., V. Kumar (2003), "The Impact of Customer Relationship Characteristics on Profitable Lifetime Duration", *Journal of Marketing*, Vol. 67 No.1, pp.77-99.

Rigby, D.K., Reichheld, F.F., and Schefter P. (2002), "Avoid the four perils of CRM", *Harvard Business Review* 80 (2): 101–109.

Rowley, J., Dawes, J. (2000), “Disloyalty: A closer look at non-loyals”, *Journal of Consumer Marketing*. **17**(6), 538–549.

Rud, O P (2001), *Data Mining Cookbook*, John Wiley & Sons, New York

Rust, R., & Zahorik, A. (1993). Customer Satisfaction, Customer Retention, and Market share. Journal of Retailing , 69 , 193-215

Rygielski, C., Wang, J., & Yen, D. (2002). Data mining techniques for customer relationship management Technology in Society , 24 (4), 483-502

Şimşek Gürsoy, U.T. (2010), Customer churn analysis in telecommunication sector *Istanbul University Journal of the School of Business Administration* Cilt/Vol:39, Sayı/No:1, 2010, 35-49

Sohn, S. and Kim, Y. (2008), Searching customer patterns of mobile service using clustering and quantitative association rule, *Expert Systems with Applications*, 34(2) pp.1070-1077

Song G, Yang, D, Wu L, Wang T and Tang, S (2006), A mixed process neural network and its application to churn prediction in mobile communications. In Proceedings of the Sixth IEEE International Conference on Data Mining Workshops (ICDM Workshops), pages 798-802

Szeinbach, S. L., J. H. Barnes & D. D. Garner (1997,) Use of pharmaceutical manufacturers´ value-added services to build customer loyalty, *Journal of Business Research,* 40:3, pp. 229-236.

Thomassey S and Fiordaliso A (2006), “A hybrid sales forecasting system based on clustering and decision trees,” *Decision Support Systems*, vol. 42, no. 1, pp. 408-421

Wei, C. and Chiu, I. (2002), Turning telecommunications call details to churn prediction: A data mining approach, *Expert Systems with Applications*, 23(2) pp.103-112

Wilson, T. D. (1995), An integrated model of buyer-seller, *Journal of Academy of Marketing Science*, 23(4), 335–345.

Zeithaml, V.A. and M. J. Bitner (2000), Services Marketing: Integrating Customer Focus across the Firm, 2nd ed., McGraw Hill, New York, NY.