DATA MINING USING FRAT-RFM ANALYSIS APPROACH FOR CUSTOMER SEGMENTATION AND PROFILING: CASE STUDY CO-OPERATIVE BANK OF KENYA

BY

JARED O. ONYUNA

MASTER OF SCIENCE IN INFORMATION SYSTEMS MANAGEMENT

2017

DATA MINING USING FRAT-RFM ANALYSIS APPROACH FOR CUSTOMER SEGMENTATION AND PROFILING: CASE STUDY CO-OPERATIVE BANK OF KENYA

BY

JARED O. ONYUNA

A DISSERTATION SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF MASTER OF SCIENCE IN INFORMATION SYSTEMS MANAGEMENT DEGREE IN THE FACULTY OF COMPUTING AND INFORMATION MANAGEMENT AT KCA UNIVERSITY

NOVEMBER, 2017

DECLARATION

This research project is my original work and has not been presented for a degree in any other University or any other award

Signature: ………………………… Date………………………………

Onyuna Jared Okinyi

This research project has been submitted for examination with our approval as the KCA University Supervisors

Signature: ……………………… … Date: ……………….. ………….

Simon N. Mwendia, PhD

This research project has been submitted for examination with my approval as the Dean Faculty of Computing and Information Management

Signature: ………………………………… Date: …………………………

ABSTRACT

With the Mobile Phones access increases rapidly and multi-channeling becoming increasingly widespread, studies of consumers will need to focus not just on understanding product choice, the reasons for channel choice but also on understanding the Recency, Frequency, Monetary and the Transaction type carried out by the customers. By using FRAT version of the RFM together with demographic attributes (gender, age, location) and data mining analysis, precise patterns can be derived for segmentation and profiling.

Companies can use customer lifetime value that consists of three factors namely: current value of customers, potential value, and customer churn. Potential value of customers focuses on the cross-selling opportunities for current customers. Therefore, cross selling models are built on the total customers of the database that is not interesting. To overcome this, we presented a framework that estimates the current and previous value and churn probability for the customers and then segmented them based on these elements and classified the customers as per their demographic and life time value attributes.

Although different approaches have been brought forward by different researchers, CRM, Customer Lifetime Value, Recency Frequency and Monetary, Size of Wallet, there is little research on incorporating different attributes in the models.

In this study we describe the customer behavior based on customers' demographic and Life Time Value attributes as a case study on a banking database. The research proposal reports on a descriptive study to identify the effectiveness of using FRAT (RFM) attributes coupled with customer demographic features for Mobile Banking Customer Segmentation and Profiling.

ACKNOWLEDGEMENT

During the past two years at KCA, I have received enormous support from the kind people around me, to whom I would like to express my sincere gratitude. First and foremost, I would like to thank my Supervisor, Simon N Mwendia PhD who have introduced me to the field of data mining and provided me with invaluable academic guidance, continuous advice and encouragement at every stage of my MSc. Project study. I cannot thank you enough. I also would wish to appreciate Prof Ngure P.K who also introduced me to Advanced Research Methods – This knowledge came in handy in step by step progress in my Research Study

I would like to thank the reviewers of my dissertation, Dr. Rimiru Richard, Dr. Mburu Lucy and Ezekiel Kuria from KCA University, for their constructive critique and comments on the manuscript. Without your knowledge and collaboration, this dissertation would have been much less than it is.

I acknowledge my gratitude to the Co-operative Bank (k) Limited for providing their data and materials for this research. I would like to express my gratitude to my colleagues at the Faculty of Computing and Information Management at KCA University for their support in various ways. Many thanks are due to the entire staff of the Faculty for administrative support.

Last but definitely not least, I'm thankful to have the constant support of my family in allowing me complete the study.

Onyuna, November 2017.

ACRONYMS

POS – Point of Sale

ATM – Automated Teller Machine

ICT – Information and Communication Technology

CRM – Customer Relationship Management

MFS - Mobile Financial Services

RFM – Recency Frequency Monetary

FRAT – Frequency Recency Amount and Type of transaction (RFM version)

LTV – Life Time Value

Operational Definition of Terms

- **Information Technology -** Information Technology (IT) has become part of necessity for human endeavors, more specifically on economic development, business transactions, quality of delivery, and productivity. IT refers to the use of software, hardware, services, and the supporting infrastructures to manage and deliver information via voice, data, and video(Safeena & Uduji, 2010;2013)
- **Customer Segmentation** – The clustering of **customers** (or prospects) into like groups.
- **Customer Profiling –** Describing a customer or set of customers as per the **demographic**, **geographic**, and **psychographic** characteristics, as well as **buying patterns**, **creditworthiness**, and **purchase history.**
- **ICT Alternative Channels-** Alternative Delivery Channels, defined as those channels that expand the reach of services beyond the traditional bank branch channel, ADCs have emerged as a result of innovations in Information and Communication Technology and a shift in consumer expectations.
- **Bank** – A bank is a financial institution that provides services such as receiving deposits, giving loan facilities (personal/Business/mortgage), and investment products; savings accounts and certificates of deposit.
- **Mobile banking -** The mobile banking is defined as "the provision of banking services to customers on their mobile devices": specifically the operation of bank current and deposit or savings accounts. According to recent research findings and forecasts in business, media and academia, mobile phones and handheld devices should have been firmly established as an alternative form of payment in most technologically advanced societies(Lee In, 2016)
- **Confidence (certainty):** Ratio of the number of transactions with all the items to the number of transactions with just the "if" items; confidence is used to Measures how often items in Y appear in transactions that contain X, in this case a confidence of 1 means all the items in Y appears in X hence an exact rule
- **Lift:** The ratio of the records that support the entire rule to the number that would be expected, assuming there was no relationship between the customers; Lift measures how many times more often X and Y occur together than expected if they were statistically independent, in this case Youth and Gender attributes

- **Leverage:** Measures the difference of X and Y appearing together in the data set and what would be expected if X and Y were statistically dependent
- **Conviction:** Compares the probability that X appears without Y if they were dependent with the actual frequency of the appearance of X without Y

Table of Contents

CHAPTER ONE

INTRODUCTION

The Background of the Research Study

Companies can use data mining techniques to identify the characteristics of the customers who will remain loyal or the churners. In banking Industry, rapid customer churn is a significant problem due to the competitive environment of this industry. (C. H. Wu, 2011) 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.

In the present day banking, there is need for total automation of banking operation and it is an imperative for all banks to attract more customers, provide efficient service and survive the competition apart from achieving the profit, which is the main goal of the business.

RFM is the Recency, Frequency and Monetary value of the customer. Data mining using FRAT-RFM analysis is a marketing approach used for analyzing customer behavioral patterns such as how recently a customer has used the service (recency), how often the customer transacts (frequency), how much the customer spends (monetary) and the value of the transaction service the customer carries out (Transaction Type – T). It is a useful method to improve customer segmentation by dividing customers into various groups for future personalization services and to identify customers who are more likely to respond to promotions.

Integration of FRAT-RFM analysis and data mining techniques provides useful information for current and new customers. ***Clustering*** based on FRAT-RFM attributes provides more behavioral knowledge of customers' actual marketing levels than other cluster analyses. ***Classification rules*** discovered from customer demographic variables and FRAT-RFM variables provides useful knowledge for managers to predict future customer behavior such as how recently the customer will probably use the service, how often the customer will use the service, and what will be the value of their services. ***Association rule*** mining based on FRAT-RFM measures, analyzes the relationships of service properties and customers' contributions and or loyalties to provide a better recommendation with the aim of satisfying customers' needs.

Customer Relationship Management (CRM) as an approach used for Segmentation and profiling does not take into consideration the Customer Lifetime Value (CLV). The CLV analyses the Recency Frequency and Monetary behaviors of the customers which are equally important attributes. Even though other approaches combine Demographic and CLV attributes for customer Segmentation and profiling, the hybrid approaches lack transaction type attribute which has been added in my study of mobile banking customer segmentation and profiling.

From the RFM analysis using the same customers and same minimum Confidence Level of 68% for association rule mining, we established that the best interesting rules achieved by introducing transaction type have higher percentage of confidence level. This indicated that transaction type attribute improves the segmentation and profiling approach. Furthermore, the accuracy level during classification improved with the inclusion of the transaction type as one of the independent attributes of Customer Lifetime Value.

1.0.2 Problem Statement

Besides the usage of demographic variables in all the stages of CRM, RFM and LTV are mostly used in customer retention and development. The combination of the variables (FRAT-RFM and demographic variables) approach therefore has not been considered enough in customer segmentation and profiling. In addition, the Co-operative Bank (k) Limited currently uses CRM system for customer segmentation and profiling (Co-opBank, 2017),which does not cover transaction types hence the use of FRAT and Demographic attributes for segmentation and profiling is of research interest.

1.0.3 Purpose of the Study

The main objective of the study is to establish the appropriate approach for customer segmentation and profiling in commercial banks in Kenya through Data Mining Using FRAT-RFM analysis and Demographic variables as independent inputs within a descriptive model.

1.0.4 Specific Objectives of the Study

- To establish the appropriate approach for mobile banking customers' segmentation and profiling by the use of customer FRAT-RFM and demographic variables.

- To evaluate the effectiveness of the approach in segmentation and profiling of mobile banking customers

1.0.5 Research Questions

- What is the appropriate approach for customer segmentation and profiling?
- What is the effectiveness of hybrid customer segmentation and profiling approach by including transaction type as an attribute?

1.0.6 Scope of the study

- This study focuses on segmentation and profiling of the customers using the ICT online channels banking outlets, mobile banking, a Technology that appeared in Kenya in recent years, which is considered a feasible alternative for delivering financial services to customers.
- Due to time limit, this research study concentrates on the behavior of customers transacting on the online ICT Alternative Channels within co-operative Bank (k) limited mainly Mobile Banking channel.
- As ICT is having a strong influence on the evolution of the financial sector as a whole, financial markets and banks, some characteristics of evolution of market segments fall within the scope of this research.

1.0.7 Significance of the Study

- This study highlights various opportunities that can be harnessed through segmentation and profiling in order to compete favorably in this increasingly competitive and unpredictable business environment. In theory this study is justified in the sense that it highlights the imperative of ICT and its inherent dynamism.
- It aims to bring attention of data miners and marketers to the importance and advantages of using FRAT- RFM analysis in data mining.
- By studying the mobile banking customers' behavior, demographic and FRAT data from mobile banking channel was used in a more efficient way with the aim to increase their profitability. Secondly, the channel was used to provide the "next best offer" for every customer segment in the most convenient way.

- This study is of great importance considering the fact that entry barriers to the banking industry have been greatly lowered by leveraging on ICT.

1.0.8 Motivations of the Study

The main motivation for this study is the customer segmentation and profiling in order to optimize the channel utilization and offer customers quality services.

- The other motivation is to understand customers' channel usage behavior. This helps in knowledge acquisition and assists in projecting future customer behaviors on mobile Banking channel with the aim of maintaining current customers and acquiring prospective ones.
- The Co-operative Bank currently uses CRM system for customer segmentation which does not take into consideration the transaction types carried out on the mobile platform, FRAT-RFM analysis takes into account the transactions done by the customer as part of segmentation of the Mobile Banking Customers.

1.0.9 The Research Study Limitations

- Due to time constraints, data collection was limited to commercial banks and specifically Co-operative Bank of Kenya limited.
- Permission was sought for the access of customer data from the relevant Data Owners for the research purposes.

1.1.0 Assumptions of the study

- The relevant Mobile Banking Data Owners shall allow access of customers' data for research purposes.
- Open source Data mining tool, Weka, with the classification and association algorithms shall be used for analyzing the customers' behavior with the aim of segmentation and profiling.

CHAPTER TWO

LITERATURE REVIEW

Introduction

Literature review chapter compares the various arguments, theories, methodologies and findings expressed in different ICT Alternative Banking research literature and try to relate the same with the study under research. The literature review Contrasts and critique the various arguments, themes, methodologies, approaches and controversies expressed in the literature.The focus of this paper is on Commercial banks in Kenya with the case study on Co-operative Bank of (K) Limited. This chapter provides the connection between various literatures and the one under study–Data Mining Using **FRAT-RFM** Analysis approach for Customer Segmentation.

2.0.1 Theoretical Literature Review

i. The Kenya Banking Sector

The Main Central Bank of Kenya's mandates under the Central Bank Act (Cap 491) is to foster the liquidity, solvency and proper functioning of a market-based financial system. This is achieved through the following:

Developing appropriate laws, regulations and guidelines that govern the players in the banking sector.

Continuous review of the banking sector laws, regulations and guidelines to ensure that they remain relevant to the operating environment. These include the Banking Act (Cap 488), Microfinance Act (2006), Central Bank of Kenya Act (Cap 491) and Prudential Guidelines and Regulations issued thereunder.

Licensing banks, non-bank financial institutions, mortgage finance companies, credit reference bureaus, foreign exchange bureaus, money remittance providers and microfinance banks.

Inspection of commercial banks, microfinance banks, non-bank financial institutions, mortgage finance companies, building societies, credit reference bureaus, foreign exchange bureaus, money remittance providers and representative offices of foreign banks to ensure that they comply with all the relevant laws, regulations and guidelines and protect the interests of depositors and other users of the banking sector.

Analysis of financial reports and other returns from banking sector players to ensure compliance with the relevant laws, regulations and guidelines. Contributing towards initiatives that promote financial inclusion.

The banking sector comprises of the Central Bank of Kenya, as regulatory authority, forty-three banking institutions (forty-two commercial banks and one mortgage finance company), eight representative offices of foreign banks, twelve Microfinance Banks (MFBs), three credit reference bureaus (CRBs), fifteen Money Remittance Providers (MRPs) and eighty foreign exchange bureaus.(CBK, 2015)

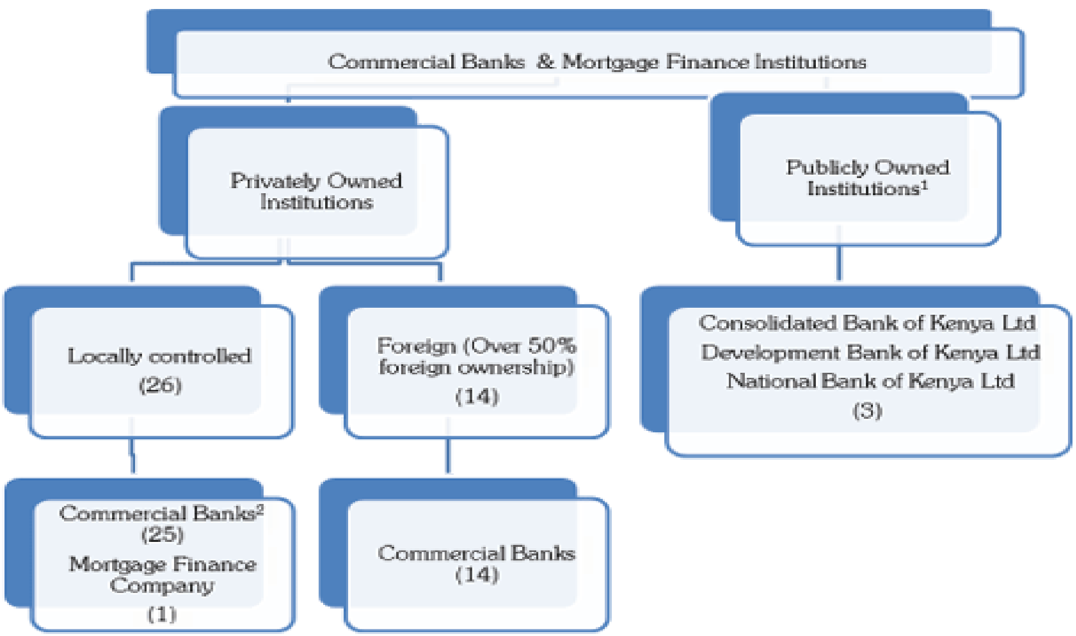


Figure 2.1: structure of licensed commercial banks and mortgage finance institutions

Source: (CBK, 2015)

ii. FinAccess Geospatial Mapping Survey (Financial Inclusion Survey)

The FinAccess Management Team comprising of CBK; Financial Sector Deepening Trust (FSD), Kenya; and the Kenya National Bureau of Statistics (KNBS) with funding from the Bill & Melinda Gates Foundation (B&MGF) conducted the FinAccess Geospatial Mapping Survey whose results and findings were released on 29th October 2015. The 2015 survey was done as a follow up of a 2013 survey to track trends in the geographical spread and outreach of the financial services touch-points. The survey estimated that 73% of the population is living within a three (3) kilometer radius of a financial services access touch point, an increase from 59% in 2013. The survey also estimated that there was a 37.9% increase in mobile money agents and 24% increase in stand-alone ATMs. The financial services access touch-points per 100,000 people also increased to 218 in 2015 compared to 162 in 2013.

This data is useful in understanding the financial inclusion landscape in Kenya. The data can assist in supporting product development and innovation; identify underserved potential markets and guide evidence-based policy decisions that bridge identified gaps in the supply and demand for financial services in general and mobile banking in particular.

2.0.2 Empirical Review

The review of empirical literature gives an evidence-based and factual analysis of related works done locally and internationally in the same area of study or related studies.

Most of the current cross-selling models were being built on the total customer database of the organization. This leads to a high overhead for building cross-selling models because the whole database contains also the data from the unprofitable customers and churners.

i. CRM Dimensions for Customer Behavior Classification

To manage the different segments of customers managers can use customer relationship management (CRM) as a leading business strategy in a competitive environment, while retention of the current customers in a competitive environment is vital for survival of the companies. CRM pursues long term relationship with profitable customers. There are different definitions in the literature for the customer relationship management, that we mention some of them here.(Ling & Yen, 2011) believe that CRM comprises a set of processes and enabling systems supporting a business strategy to build long term, profitable relationships with specific customers. (Hujun Yin, 2014) defined CRM as an enterprise approach to understand and influence customer behavior through meaningful communications in order to improve customer acquisition, customer retention, customer loyalty, and customer profitability.(Sheth, 2011) 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. It involves the integration of marketing, sales, customer service, and the supply chain functions of the organization to achieve greater efficiencies and effectiveness in delivering customer value.

Increased customer retention and loyalty, higher customer profitability, creation value for the customer, customization of the products and services, and lower process, higher quality products and services are mentioned as the potential benefits of CRM (Jerry Fjermestad, 2015). Marketers believe that 80% of the profits are produced by to 20% of profitable customers and 80% of the costs are produced by top 20% of unprofitable customers. This rule is called the 80/20 rule that the marketers use it for customer profitability evaluation. By these definitions it may seem that CRM is only useful for managing the relationships between businesses and customers. A closer examination revealed that CRM is also applicable to business-to-business environments.

All these definitions emphasized on the importance of customer acquisition and retention through business intelligence to provide value to the organization and customers. It is therefore implied that customer acquisition is more expensive than customer retention because the lack of information on new customers makes it difficult to target the appropriate customers. Therefore, precise evaluations of customer value and customer segmentation and profiling using a hybrid approach is important.

ii. Weighted RFM Model

In recent years, several researchers have considered RFM variables in developing clustering models. For example, (Hosseini & Maleki, 2011) combined weighted RFM model into K-Means algorithm to improve Customer Relationship Management (CRM) for enterprises. (V. Vijayakumar, 2016) applied RFM model and K-Means method in the value analysis of the customer database of an outfitter in Taiwan to establish strong relationship and eventually consolidate customer loyalty for high profitable long-term customers. (Chuang, 2012) first assessed the weights of R, F, and M in order to know their relative importance by Analytical Hierarchy Process method, then evaluated Customer Lifetime Values (CLV) by clustering analysis and finally, sorted customers by self-organizing map method to recognize their behavior.

iii. RFM LTV and Demographic Variables Model

Demographic variables, RFM, and LTV are the most common input variables used in the literature for customer segmentation and clustering (Mo Et al, 2011).

Although customer segmentation and market segmentation have many similarities, there are some critical differences regarding their input variables for their clustering mechanisms (Namwar et al., 2011). Market segmentation usually aims at acquiring new customers, and deals with the first step of CRM (i.e. customer acquisition) using socio-demographic data, but, customer segmentation is used at all steps of CRM using both socio-demographic and transactional data.

iv. Size of Wallet (SOW) and Share of Wallet

Customer value issue is an important part of CRM. There are several methods to find customer value. These methods divided to **popular metrics** and **strategic metrics**. Some of popular customer-based value metrics contains Size of Wallet (SOW), and Share of Wallet (SW). SOW refers to "total volume of a customer's spending in a category". SW refers to "proportion of category volume accounted for by a brand or focal firm within its base of buyers" (Johnson et al, 2015). Du, Kamakura, and Mela have combined SOW and SW and segmented customers to develop effective strategies in each group and have identified the valuable customers (Erdem Tulin, 2016). Strategic metrics contains RFM, Past Customer Value (PCV) and Life Time Value (LTV).

v. RFM analysis

RFM analysis has been used in direct marketing for several decades (Kurt Ruf, 2013). This technique identifies customer behavior and represents customer behavior characteristics by three variables as follows:

- **Recency**: refers the duration time between last customer purchasing and present time.
- **Frequency**: refers the total number of customer purchasing during life time.
- **Monetary**: refers the average money spending during past customer purchases.

A comprehensive customer segmentation method would be used in customer acquisition as well as customer retention and development. (M. Namvar et al, 2011), in their study on An approach to optimized customer segmentation and profiling using RFM, LTV, and demographic features, found that, Churn avoidance, complaint management, one to one marketing, etc., would be so more accurate with thorough customer segmentation. Besides, an effective customer profiling will complement the customer segmentation in order to design marketing strategies. Undoubtedly, to achieve comprehensive customer segmentation and customer profiling, input variables and their sequence, segment's evaluation and their visualization are so important.

(Birant et al..., 2011), used a novel three-step approach which uses RFM analysis in three data mining tasks: clustering, classification and association rule mining, applied one after another. **Firstly**, customer segments with similar RFM values are identified to be able to adopt different marketing strategies for different customer segments. **Secondly**, classification rules are discovered using demographic variables (age, gender, location etc.) and RFM values of customer segments to predict future customer behaviors and to target customer profiles more clearly. **Thirdly**, association rules are discovered to identify the associations between customer segments, customer profiles and product items purchased, and therefore to recommend products with associated rankings, which results in better customer satisfaction and cross selling. In the proposed approach, it is possible to predict the customer segment of a new customer from classification rules, according to their profile, and then a recommendation list can be generated according to their predicted segment.

Using a Hybrid Segmentation Approach for Customer Value (Fatemeh A. K. Et al, 2014), developed a two-phase clustering model based on k-means algorithm and SOM techniques where k was optimized for 340 customers of a chain store. In application of the method on their case study (in chain stores industry), the existing customers were divided into 34 groups of customers according to their shared transactional behavior and demographic characteristics. Profiles of customers in each group could be analyzed by marketers to make strategies for each group. Beyond simply understanding customer value in each cluster, the chain stores would gain the opportunities to establish better customer relationship management strategies, improve customer loyalty and revenue and find opportunities for up and cross selling.

2.0.3VariousApplied Approaches used for Customer Segmentation and Profiling

i. RFM Analysis

(Birant et al..., 2011)proposed a new three-step approach which uses RFM analysis in data mining tasks, including clustering, classification and association rule mining, to provide market intelligence and to assist market managers in developing better marketing strategies. In their model, (i) once clustering task is used to find customer segments with similar RFM values, (ii) then, using customer segments and customer demographic variables, classification rules are discovered to predict future customer behaviors, (iii) finally; association rule mining is carried out for product recommendation. The proposed model depends on the sentence "the best predictor of future customer behavior is past customer behavior". (Cockrum, 2011).

According to this experimental study results on Data Mining Using RFM Analysis, the proposed approach provided better product recommendations than simple recommendations, by considering several parameters together: customer's segment, the current RFM values of the customer, potential future customer behavior and products frequently purchased together.

ii. RFM LTV and Demographic Variables

An approach to optimize customer segmentation and profiling using RFM, LTV, and demographic features study was carried out by (Namwar et al., 2011). In this approach, first,different combinations of RFM and demographic variables are used for clustering. Second, using LTV, the best clustering is chosen. Finally, to build customer profiles each segment is compared to other segments regarding different features. The approach was applied to a dataset from a food chain stores and resulted in some useful management measures and suggestions. The results revealed that the most valuable segment was a relatively small segment with a low annual income, a moderate number of cars owned, and a moderate level of education and occupation. In other words, the income of target food chain store was mostly due to their average customers. Besides, the largest segment had a low amount of average LTV.

iii. Incremental Weighted RFM Mining

Due to the problem which is suffered from inefficiency by reprocessing of the data which have already been processed in incremental data in which new data are added persistently in the existing recommendation system for u-commerce using association rules, (Young Sung Cho et al ..., 2013)proposed a new incremental weighted mining for recommending prediction in emerging data environment in order to improve the accuracy of recommendation with high purchase.

The proposing method can extract frequent items and create weighted association rules using incremental weighted mining based on RFM analysis rapidly when new data are added persistently in order to predict frequently changing trends by emphasizing the important items with high purchase according to the threshold for creative weighted association rules in u-commerce. To verify improved better performance of proposed system than the previous systems, the researchers carried out the experiments in the same dataset collected in a cosmetic internet shopping mall. It was meaningful to present a new methodology of weighted mining for recommendation system in emerging data under ubiquitous computing environment. Furthermore, it was an interesting research area on the aspect of effectiveness for recommendation system being that weighted mining was applied after SOM clustering using RFM analysis.

iv. Length RFM Relationship Model - LRFM

(Mohsen Alvandi et al..., 2012)in their study approach using K-Means Clustering Method For Analyzing Customer Lifetime Value With LRFM Relationship Model In Banking Services in Iran considered LRFM customer relationship model which consists of four dimensions: relation length (L), recent transaction time (R), buying frequency (F), and monetary (M) to cluster customers, analyzing and calculating CLV of different clusters. Then cluster with homogeneous CLV incorporate and construct a special cluster. Finally the clusters were ranked based on their CLV scores. There were two types of data in this study: transactional data, consist of relation length (L), recent transaction time (R), buying frequency (F), monetary (M) and customer lifetime value (CLV) and behavioral data, consist of: account number, customer type, account type, account status, first transaction and last transaction.

Below were the results of ranking customers and the appropriate strategy for each cluster:

Customers with L↑R↑F↑M↑ pattern: These customers are in the highest rating category of CLV, so bank must provide specific services for these valuable customers. Cluster A called potential loyal customers.

Customers with L↑R↓F↓M↑ pattern: These are valuable customers for bank but their loyalty is low, so may in the future turn to other banks. CLV score of this group is high between our customers. Cluster B is called platinum customers.

Customers with L↓R↑F↓M↓ pattern: This pattern show that these customers have low length of relation and frequency, high distance between transaction and monetary value is low also. CLV score of this group is low, so these customers are not valuable for bank. Cluster C called uncertain lost customers.

Customers with L↑R↓F↓M↓ pattern: These customers have long length of relationship but **recency**, **frequency** and **monetary** value of them does not follow a specific pattern. Lowest score of CLV belong them in this study. These customers recently joined the bank, so should be protected if the bank wants to have a long relation in future. Cluster D called low consumption cost customers.

Customers with L↑R↑F↑M↓ pattern: according to high L, R and F, if monetary values of these customers increase, it can be expected that CLV score will increase until highest in future. Cluster E called potential high frequency customers.

Customers with L↓R↑F↓M↑ pattern: These customers have highest CLV after cluster A, so they are valuable for the bank. Although length of relation and frequency are low but recency and monetary are high. Cluster F called consumption lost customers.

Customers with L↓R↓F↓M↓ pattern: These customers join us recently so have L, R, F and M in the lowest value. CLV score of this group is low also. Bank should have some persuasive plans for preserve of them. Cluster G called uncertain new customers.

Customers with L↓R↓F↑M↓ pattern: These customers have high loyalty but for low monetary and length of relationship their CLV score is very low. So bank should propose specific options for increase of their monetary. Cluster H called frequency promotion customers.

Customers with L↑R↓F↑M↓ pattern: Customers of this group have high transaction with bank but monetary and recency value of them are low. This group has high CLV score so Bank needs to provide better services to maintain them. Cluster I called high frequency buying customers.

The accuracy of the segmentation and profiling is achieved by increasing the minimum confidence level towards 100% during association mining using Apriori algorithm for best interesting rules

In conclusion, even though different studies provided market intelligence for marketers, they did not take into consideration the type of goods/services purchased by the customers which are an important variable in customer segmentation and profiling in providing more accurate market intelligence. This is the additional variable which was used in the model to provide more accurate results on the segmentation and profiling of the mobile banking customers.

2.0.4 Sample Approaches used by Banks for Segmentation and Profiling in Kenya

i. Equity Bank – CRM

For an organization to succeed in implementing Customer relationship Management, CRM, Management commitment in terms of strategies and plans is very important.

Management of Equity Bank in ensuring effective implementation of the Customer Relationship Management. This was through observing the existing bank rewards and motivation policies, customers satisfaction on the services provided by bank and whether the services meet their expectations and demands, turnaround time (TAT) for services provided by the bank.

The bank is in a better position for implementation of CRM with existing policies which support good customer services. The bank has established contact centers, customers experience centers where all customers' complaint are channeled.

The recommendation is to incorporate Frequency, Recency, Monetary as well as the Type of services carried out by the customers to give a full picture of the customers' behavior with the objective of Segmentation and profiling.

(source http://www.ke.equitybankgroup.com/)

ii. KCB - CRM and LTV

CRM in the early days of the Commercial Bank of Kenya operations was not emphasized since the organization was fully run by government and its business strategy was not geared towards customer centrism. The organization operated from inside out and was blurred by a lot of bureaucracy and insensitivity towards customers. In fact for several years the bank operated at a loss despite being monopolistic in nature because competition was very low making the bank largely unconcerned about building customer relationships.

The implementation of CRM in banking sector is focused on the evaluation of the critical satisfaction dimensions and the determination of customer groups with distinctive preferences and expectations in the private bank sector.

CRM and LTV implementation in Kenya Commercial Bank enable the distribution channel, as well as all departments, to work together and share information about customers. This means that every employees and departments work together to ensure customers are the center in any activity they are doing and hence increase retention and royalty of the customers towards bank's products. The goal of collaborative CRM then is maximum sharing of relevant information acquired by all departments with the focus on increasing the quality of services provided to customers.

The Bank only implemented CRM and Customer Life Time Value and left out the other important features of the customer like how frequency the customer uses the service and the type of the service used. These can add more value to customer segmentation.

(source https://kcbgroup.com/)

iii. BBK - Customer Life Time Management (CLM) and CRM

It is common knowledge in business circles that it is significantly cheaper to retain existing customers than to acquire new ones. By providing employees with quick access to actionable customer data, organizations better identify the right customers, increase their loyalty, and maximize their profitability.

Effective customer retention begins with knowledge. Companies assemble a complete customer profile that allows users to see all demographic data, interactions, communications, and purchases made.

This information, combined with robust segmentation and analysis tools, enables organizations to better gauge the profitability of each customer.

Establishing customer loyalty is only half of the equation. Organizations maximize the profitability of their existing customers and better capitalize on revenue opportunities.

Organizations use robust segmentation and data mining capabilities to identify trends and patterns that indicate key selling scenarios based on buying behavior, demographics, or other criteria.

Taken to another level, Barclays Bank (k) Limited leverage leading indicators such as lifetime value (LTV) or Customer Lifetime Management (CLM) to predict future profitability and use that information as the basis for more accurate lead scoring and effective sales engagement. In today's economy, it is imperative that organizations not only maximize the value of existing customers but also win new business in order to establish a foundation for sustainable growth. One of the most effective ways to maximize revenue opportunities is by optimizing the marketing mix. But in order to do that, marketing departments need end-to-end visibility into marketing data through a unified CRM application. This visibility enables organizations to determine lead-to revenue metrics and understand their true ROMI (return on marketing investment).

That in turn allows them to more tightly link demand generation activities to sale execution, with the ability to adjust tactics as conditions change. Targeting the right prospects from the start is one of the fastest ways to reduce waste and improve campaign effectiveness.

More accurate customer segmentation, lead qualification, and lead scoring based on insightful customer data helps companies focus on prospects most likely to buy. Better targeting alone is not enough. And when marketing capabilities are part of a holistic CRM solution, organizations easily track their effectiveness and quickly adjust the channel or messaging to improve results. But these capabilities shouldn't be limited to traditional channels.

(source https://www.barclays.co.ke)

2.0.5Theoretical framework

Several authors have further identified the benefits of mobile and online banking in terms of ubiquity coverage, flexibility, interactivity, and with greater accessibility compared to conventional banking channels such as Automated Teller Machine (ATM), and non-mobile banking(Sim, 2011). Despite heavy investment by banks in developing online capabilities, many online consumers are inactive or use online banking sporadically, focusing mainly on verification tasks and avoiding more complex transactions. As moving consumers to the online channel has a clear cost savings goal, succeeding in this objective becomes very important for bank services providers, as meaningful savings are only possible with a significant migration of consumers to online banking.

Theories on ICT Alternative Banking Channels Transactions Behavior

a) Innovation Diffusion Theory (IDT)

Diffusion of innovations is a theory that seeks to explain how, why, and at what rate new ideas and technology spread. (Everett Rogers, 2011), a professor of communication studies, popularized the theory in his book Diffusion of Innovations; the book was first published in 1962. Rogers argues that diffusion is the process by which an innovation is communicated over time among the participants in a social system. The origins of the diffusion of innovations theory are varied and span multiple disciplines.

Rogers proposes that four main elements influence the spread of a new idea: the **innovation itself**, **communication channels**, **time**, and **a social system**. This process relies heavily on human capital.

The innovation must be widely adopted in order to self-sustain. Within the rate of adoption, there is a point at which an innovation reaches critical mass.

b) Theory of Reasoned Action

According to (Michael Hennessy, 2012), behavioral intention is expected to predict actual behavior accurately if the following three boundary conditions, specified by the theory, can be held:

i. The degree to which the measure of intention and the behavioral criterion correspond with respect to their levels of specificity of action, target, context and time frame.

ii. The stability of intentions between time of measurement and performance of the behavior and

iii. The degree to which carrying out the intention is under the volitional control of the individual (i.e., the individual can decide at will to perform or not to perform the behavior).

The components of TRA are three general constructs: Behavioral intention (B1), Attitude (A), and subjective norm (SN).

TRA depends on the person's attitude about the behavior and subjective norms (B1 = A + SN).

If a person intends to do a behavior then it is likely that the person will do it. Behavioral intention measures a person's relative strength of intention to perform a behavior.

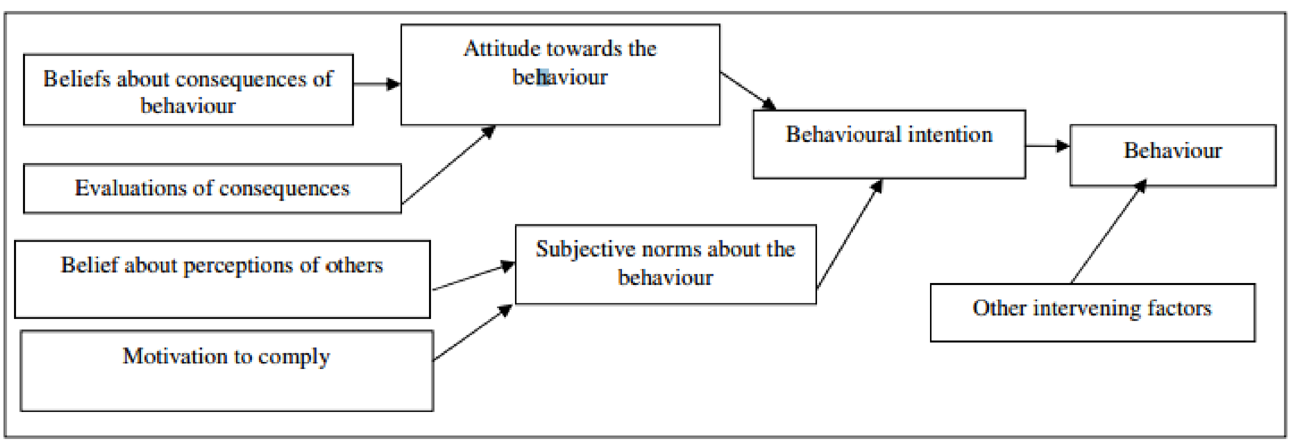


Figure 2.2: Theory of Reasoned Action

c) Technology Acceptance Model (TAM)

TAM has been the most influential theoretical tool for explaining the user's acceptance of technology (Al-Ajam and Khatil, 2013). The purpose of this model therefore is to predict the acceptability of a toll and to identify the modifications which must be brought to the system in order to make it acceptable to users.

In fact, TAM is the most widely used model to explain computer usage behavior as relates to technology adoption. This model suggests that the acceptability of an information system is determined by two main factors:

Perceive ease of use and perceived usefulness - Perceived usefulness is defined as being the degree to which a person believes that the use of a system will improve his performance, and perceived ease of use refers to the degree to which a person believes that the use of a system will be effortless. (www.edu.tech.wiki.com).

Specially, TAM proposes two beliefs- perceived ease of use and perceived usefulness that determined one's behavioral intention to use a technology. Behavioral intention is a major of the strength of one's intension to perform a specified behavior.

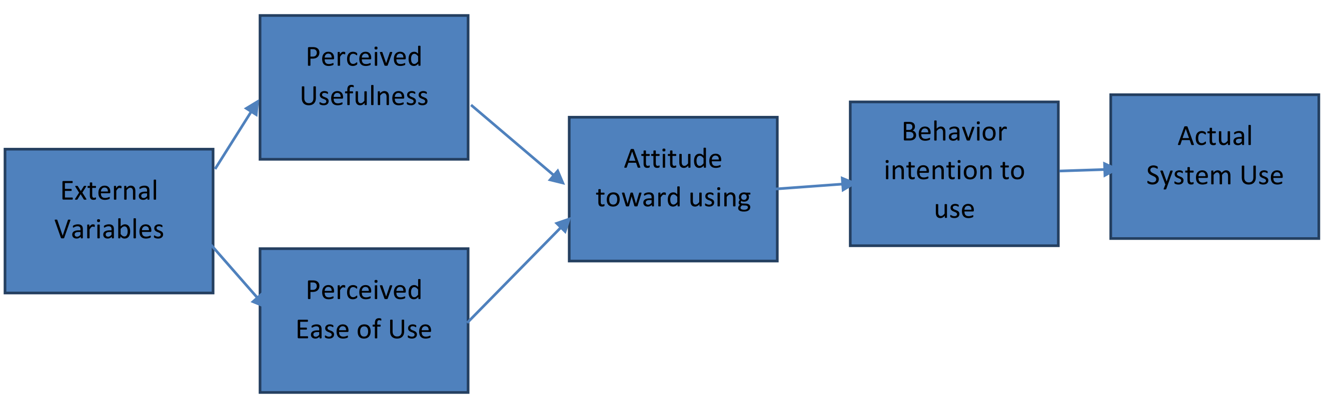


Figure 2.3: Technology Acceptance model

2.0.6 Conceptual Framework

This section presents a new three-step approach which uses FRAT-RFM analysis in data mining tasks. In the approach, (i) once clustering task is used to find customer segments with similar RFM values, (ii) then, classification rules are discovered using demographic variables (age, gender, location etc.) and FRAT values of customer segments to predict future customer behaviors, (iii) finally; association rule mining is carried out for product recommendation.

The proposed model can assist managers in developing better marketing strategies that fully utilize the knowledge resulting from data mining and FRAT-RFM analysis. It is useful for predicting customer behaviors according to their demographic variables, because not all customers have transacted identical amounts, some have transacted more often, and some have transacted more recently.

In addition, it provides better product recommendations than simple recommendations, by considering several parameters together: customer's segment, the current FRAT-RFM values of the customer, potential future customer behavior and transactions frequently done together.

Simplified Conceptual Framework diagram

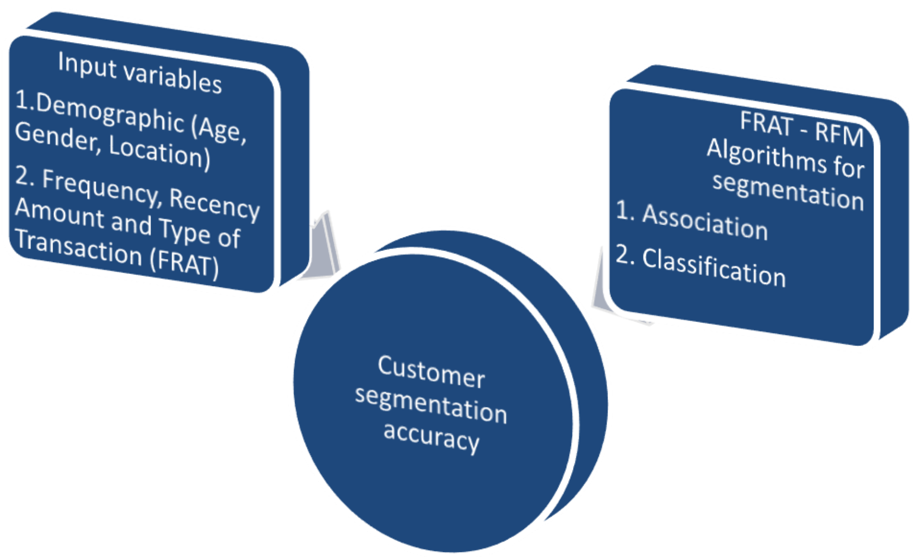


Figure 2.4: Conceptual Framework

VARIABLE	SUB-VARIABLE	INDICATORS	VALUES
Input Variables	Demographic Variables	Age Group	Youth (< 35) Adult (36 - 55) Senior (56+)
		Gender	Male Female
		County (Location)	Nairobi MOMBASA Kisumu ELDORET
Customer Segmentation Approaches	FRAT- RFM and Data Mining	Classification Tasks Clustering Tasks Association Tasks, Customer segmentation accuracy	Classification rules Customer segments Associations Rules Use of minimum confidence level close

			to 100% during Association Rule Mining by Apriori Algorithm

Table 2.1: The Operationalization Table

CHAPTER THREE

RESEARCH METHODOLOGY

3.0.1 Overview

The research methodology chapter introduces the overall methodological approach that was adopted in coming up with a descriptive model for Mobile Banking customer profiles within commercial banks in Kenya. The chapter also indicated how the methodology approach fitted the overall research design. It also explained the sampling technique employed, the target population, data collection method used and how the results were analyzed and interpreted.

3.0.2 The Method for Achieving Objective One

a) Research design

A quantitative case study was adopted for this study. According to (Yin R. K., 2014), a case study allows deep understanding of the research area the researcher is focusing on. The case study research design was carried out in Co-operative Bank (k) Limited, and it shall allow both quantitative and qualitative analyses of the data collected. Several literature surveys of Customer Segmentation and profiling were also conducted.

b) Target population

The target population was the customers who have registered for mobile banking services with Co-operative Bank in the five regions of Nairobi, Mombasa, Nakuru, Eldoret and Kisumu between 1st Jan 2015 and 31st July 2017totaling to 426,908.

c) Sampling Technique

In the study we used purposive sampling technique. Purposive sampling is where the researcher chooses the sample based on who they think would be appropriate for the study. This is used primarily when there is a limited number of people that have expertise in the area being researched

d) Sampling Size

Stratified Sampling was used where the population was partitioned into groups based on a factor that influences the variable that is being measured.

These groups are then called strata. An individual group is called a stratum. With stratified sampling one should:

- partition the population into groups (strata)
- obtain a simple random sample from each group (stratum)
- collect data on each sampling unit that was randomly sampled from each group (stratum)

Stratified sampling works best when a heterogeneous population is split into fairly homogeneous groups. Under these conditions, stratification generally produces more precise estimates of the population percent than estimates that would be found from a simple random sample.

e) *Data collection methods*

The study used primary data from the Bank Data Warehouse system containing registered Active Mobile customers. No questionnaires or interviews were conducted for this study.

f) Data Analysis

Qualitative Data Analysis (QDA) is the range of processes and procedures whereby we move from the qualitative data that have been collected, into some form of explanation, understanding or interpretation of the people and situations we are investigating in our case mobile banking customers at Co-operative Bank (k) Limited.

3.0.3 The Method for Achieving Objective Two

a) Research design

A quantitative case study was adopted for this study. According to (Yin R. K., 2014), a case study allows deep understanding of the research area the researcher is focusing on.

Case study design are the hallmarks of a post-positivist approach to research: seeking rival explanations and falsifying hypotheses, the capability for replication with a multiple case study design, the pursuit of generalizations (if required), minimizing levels of subjectivity, and the use of multiple methods of qualitative and quantitative data collection and analysis. While objectivity is a goal, YIN also recognizes the descriptive and interpretive elements of case study. According to YIN what makes case study research distinct from experimental studies is the case study is investigated in context, examined in its "real world setting"

How the methods are used vary and depend on the research purpose and design, which is often a variation of a single or multiple case study research design. Interviews and focus groups, observations, and exploring artifacts are most commonly employed to collect and generate data with triangulation of methods and data.

b) Target population

The target population were the customers who have registered for mobile banking services with Co-operative Bank in the five regions of Nairobi, Mombasa, Nakuru, Eldoret and Kisumu between 1st Jan 2015 and 31st July 2017 totaling to 426,908.

c) Sampling Technique

Stratified Samplingwas used where the population was partitioned into groups based on a factor that influences the variable that is being measured.

These groups are then called strata. An individual group is called a stratum. With stratified sampling one should:

- partition the population into groups (strata)
- obtain a simple random sample from each group (stratum)
- collect data on each sampling unit that was randomly sampled from each group (stratum)

d) Sample

A sample data size of 1212mobile banking customers was selected for analysis covering the whole attributes captured in the independent variables.Out of the sampled data n-1 folds were run for training per each iteration and the rest was used as testing data in cross validation approach where n=12.

e) Data collection methods

The study will use primary data from the Bank systems containing registered Active Mobile customers. No questionnaires or interviews was conducted for this study.

3.0.4 Pilot Data

A sample data of 13 customers from 3 different locations (Nairobi, Mombasa and Kisumu), Gender (Male, Female) and different ages (Youth, Adult, Senior) have been collected for piloting.

The preprocessed demographic data with the Age, Gender and Location attributes

CUSTOMER-ID	AGE	GENDER	LOCATION
CUSTOMER001	ADULT	Male	MOMBASA
CUSTOMER002	SENIOUR	Male	NAIROBI
CUSTOMER003	YOUTH	Female	KISUMU
CUSTOMER004	YOUTH	Female	NAIROBI
CUSTOMER005	ADULT	Male	MOMBASA
CUSTOMER006	YOUTH	Female	MOMBASA

Table 3.1 Demographic Attributes

In the proposed approach, it is assumed that all the required tasks except feature selection and extraction are conducted for the data in 'Customers' Transactions' and 'Customers' Profiles' databases. So, these two more significant and innovative points are used here.

The significant point was the coefficients of **Recency, Frequency, Monetary and Transaction type** variables in calculating the RFM - FRAT scores. As a result of this step, determinant demographic features of customers and their RFM values are extracted and prepared for next step.

The transaction types taken into consideration and their numeric strength scoring equivalent (1 – 5 with 5 highest score and 1 least score) were graded as below per the more revenue generated by a type of a transaction.

	Transaction_Type	**Grading Score**
1	Balance_Enquiry	1
2	Cash_Withdrawal	1
3	Mini_Statement	1

4	Full_Statement	1
5	Top_Up	2
6	Bill_Payment	3
7	Mobile_Money	4
8	Funds_Transfer	5

Table 3.2 Transaction Type Scoring

The sum of the scoring was then used to get the aggregate weight for the Transaction Type attribute for the RFM – FRAT.

Weights were also determined for Frequency, Recency and Monetary (Amount)

The cumulative totals for all the attributes F, R, A and T give the Customer Lifetime Value CLV.

RFM – Segmentation pilot Data

SEGMENTS	FREQUENCY WEIGHTS	RECENCY WEIGHTS	AMOUNT WEIGHTS	TRANSACTION TYPE WEIGHTS	F.R.A.T	WEIGHT-NOTATIONS	SUM OF WEIGHTS	CUSTOMERVALUE
CLUSTER001	4	5	5	4	4554	R↑F↑M↑T↑	18	BestLoyalCustomer
CLUSTER002	5	4	2	3	5423	R↑ F↑M↓T↑	14	ValuableCustomer
CLUSTER003	2	5	3	2	2532	R↓ F↑M↑T↓	12	ValuableCustomer
CLUSTER004	2	4	2	4	2424	R↓ F↑M↓T↑	12	ChurnCustomer
CLUSTER005	2	3	4	3	2343	R↓ F↑M↑T↑	12	ChurnCustomer
CLUSTER006	2	4	3	2	2432	R↓ F↑M↑T↓	11	ChurnCustomer
CLUSTER007	1	2	1	1	1211	R↓ F↓M↓T↓	5	UncertainCustomer

Table 3.3 FRAT attributes

The table below shows the combined csv document for the demographic and RFM scores for classification and association processes.

AGE	GENDER	LOCATION	CUSTOMERVALUE
ADULT	Male	MOMBASA	ValuableCustomers
SENIOUR	Male	NAIROBI	ValuableCustomers
YOUTH	Female	KISUMU	ValuableCustomers
YOUTH	Female	NAIROBI	BestLoyalCustomers
ADULT	Male	MOMBASA	BestLoyalCustomers
YOUTH	Female	MOMBASA	ValuableCustomers
YOUTH	Female	KISUMU	ValuableCustomers
ADULT	Male	KISUMU	UncertainCustomers

Table 3.4 Combined FRAT and Demographic Attributes

The above was then converted to .arff (Attribute-Relation File Format) file which is an ASCII text file that describes a list of instances sharing a set of attributes.

customers-pilot.arff

```
@RELATION customers-pilot

@attribute AGE{YOUTH,ADULT,SENIOUR}
@attribute GENDER{Male,Female}
@attribute LOCATION{MOMBASA,KISUMU,NAIROBI}
@attribute CUSTOMERVALUE{ValuableCustomers,BestLoyalCustomers,UncertainCustomers}

@DATA
ADULT,Male,MOMBASA,ValuableCustomers
SENIOUR,Male,NAIROBI,ValuableCustomers
YOUTH,Female,KISUMU,ValuableCustomers
YOUTH,Female,NAIROBI,BestLoyalCustomers
ADULT,Male,MOMBASA,BestLoyalCustomers
YOUTH,Female,MOMBASA,ValuableCustomers
YOUTH,Female,KISUMU,ValuableCustomers
ADULT,Male,KISUMU,UncertainCustomers
ADULT,Male,KISUMU,UncetainCustomers
ADULT,Female,NAIROBI,UncertainCustomers
ADULT,Female,NAIROBI,ValuableCustomers
ADULT,Male,MOMBASA,ValuableCustomers
ADULT,Female,NAIROBI,BestLoyalCustomers
```

Preprocessing and loading into Weka for processing

Data preprocessing step is needed to make knowledge discovery easier and correctly. Data preparation operations such as reduction in number of attributes, outlier detection, normalization, discretization, concept hierarchy generation significantly improve the model; in fact a further increasing the prediction accuracy and saving in elapsed time.

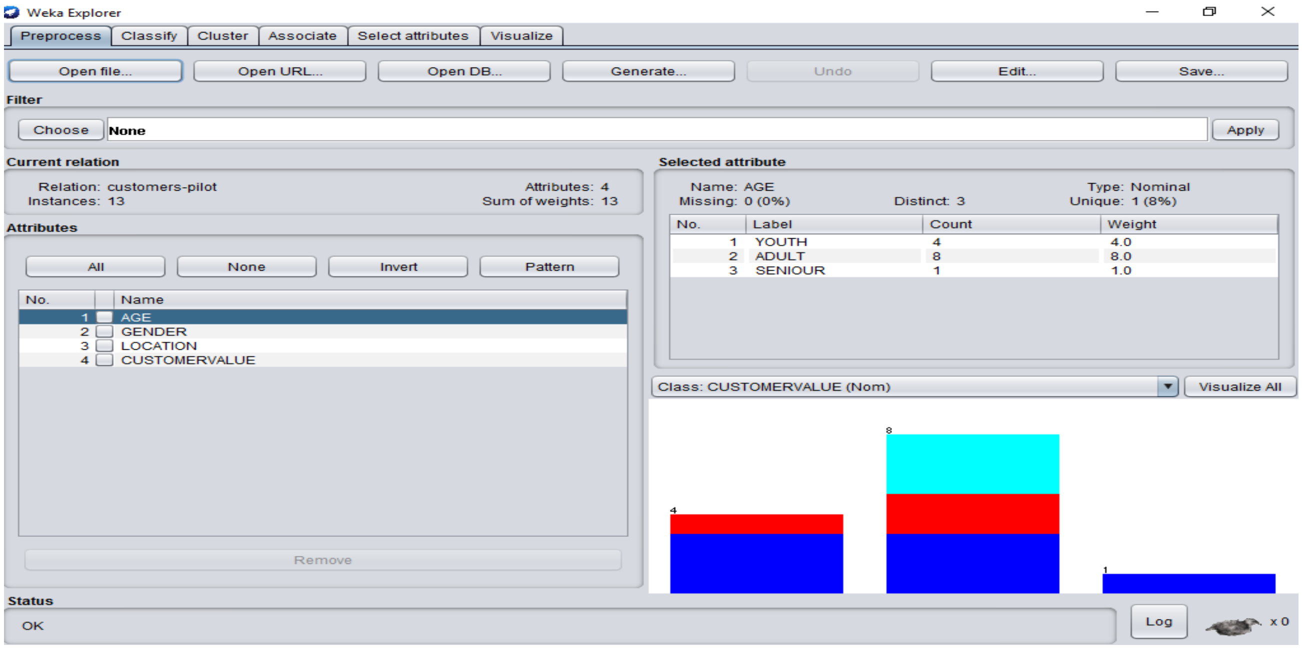


Figure 3.1 Pre-processing

Classification output using percentage split of 66% for testing and 34% training runs

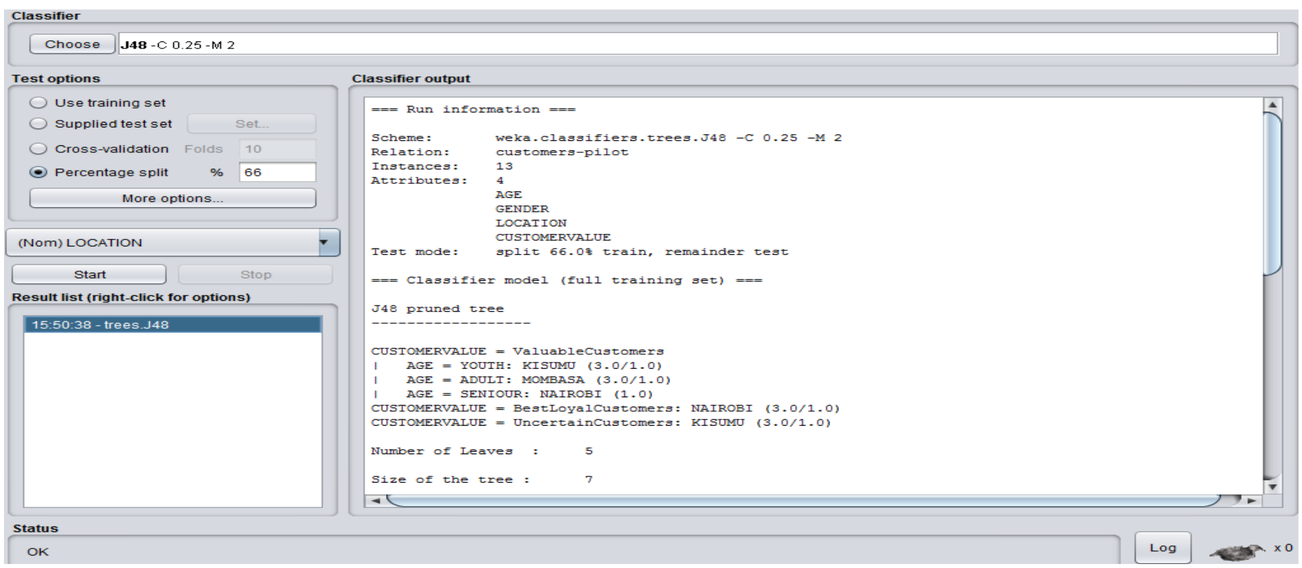


Figure 3.2 Classification using J48 Algorithm

customers-pilot.arff

The tree visualization of the predictive classification model

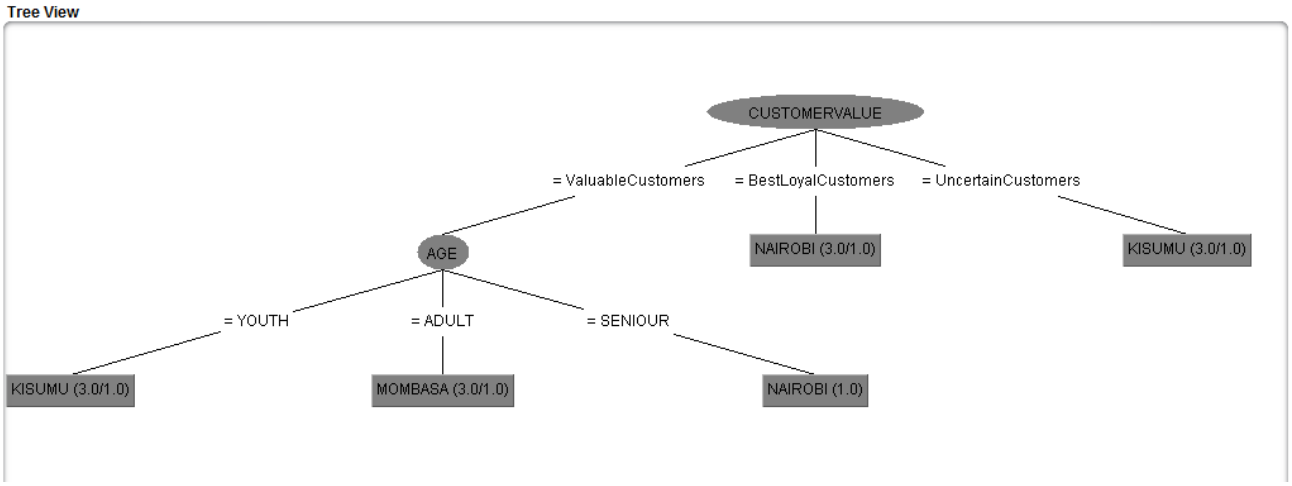
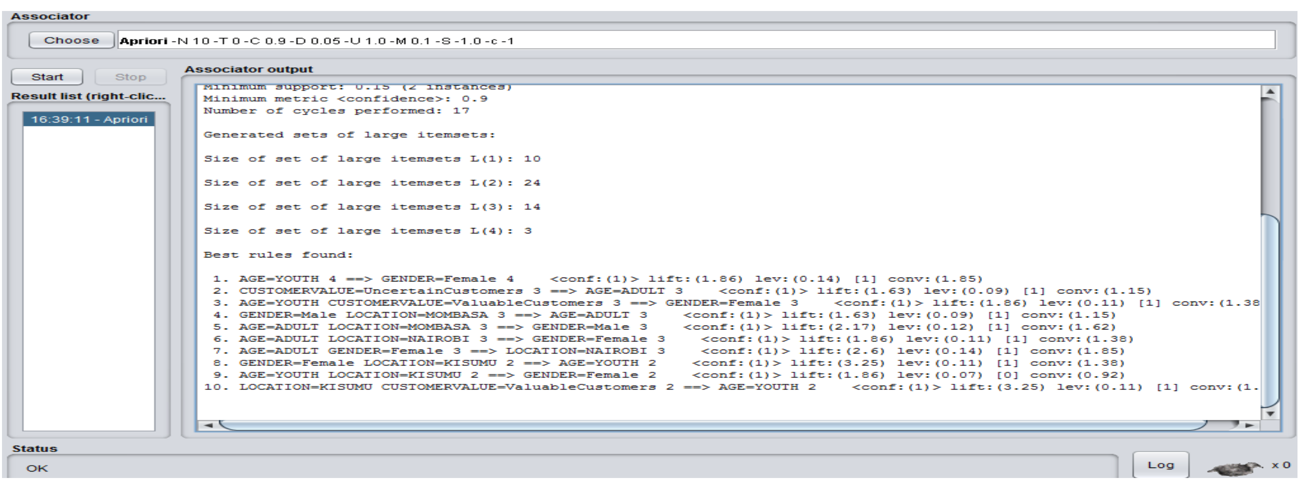


Figure 3.3 Pruned Tree for the pilot Data (6 – Leaves. size – 7)

Figure below shows 10 best classification rules found that identify customer profiles and the associated FRAT-RFM values.



3.0.5 Data analysis

The data will be examined comprehensively for completeness. Data analysis consists examining, categorizing and testing the evidence collected to address the propositions of the study (Yin R. K., 2014).Pattern matching technique was adopted in this case, (Yin R. K., 2014)compares the collected evidence against the initially stipulated pattern.

CHAPTER FOUR

DATA ANALYSIS, RESULTS AND DISCUSSION

4.0.1 INTRODUCTION

Customer segmentation is the practice of dividing a customer base into groups of individuals that are similar in specific ways relevant to marketing such as age, gender, interests, spending habits, and so on. One of the easiest definitions is "a group of customers with shared needs". From this definition, it's clear what we need to do is to identify customers with shared needs. The customer segmentation consists of two phases. First phase includes K-Means clustering, where the customers are clustered according to their FRAT-RFM (Recency Frequency Monetary and Transaction Type). In the second phase, with demographic data each cluster is again partitioned into new clusters. Finally LTV (Life Time Value of the customers) are used to generate customers' profile.

The chapter comprises of the Data Analysis, preprocessing, processing through Classification and Association algorithms to determine predictive patterns or behavior of the customers and the Study findings.

4.0.2 DATA ANALYSIS

Objective one results

The Objective one of this study was to establish an appropriate approach for customer segmentation and profiling by the use of customer FRAT- RFM and demographic variables.

From literature review we established that all the reviewed approaches have not taken transaction type into consideration as one of the attributes.

Below is the Classification and Association output done using J48 and apriori algorithms respectively to compare the data processing, segmentation and profiling without the transaction type using cross validation with n=12

From this we have established that all of the class attributes have zero accuracy parameters except NEW customer value class attribute for the classification rule. The tree also generated only one leaf when CUSTOMERVALUE class is used for processing. In the association rule for the same data, the best rule had 74% certainty as opposed to the 76% certainty achieved by including transaction type where Minimum Confidence is set to 68% for both.

=== Run information ===

Scheme: weka.classifiers.trees.J48 -C 0.25 -M 2
Relation: mobile-banking-data-T
Instances: 1212
Attributes: 4
REGION
GENDER
AGE
CUSTOMERVALUE
Test mode: 12-fold cross-validation

=== Classifier model (full training set) ===

J48 pruned tree

: NEW (1212.0/503.0)

Number of Leaves: 1

Size of the tree: 1

Time taken to build model: 0.01 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances	709	58.4983 %
Incorrectly Classified Instances	503	41.5017 %
Kappa statistic	0	
Mean absolute error	0.2347	
Root mean squared error	0.3425	
Relative absolute error	99.8373 %	
Root relative squared error	99.9996 %	
Total Number of Instances	1212	

=== Detailed Accuracy By Class ===

TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	PRC Area	Class
0.000	0.000	0.000	0.000	0.000	0.486	0.050	VALUABLE
1.000	1.000	0.585	1.000	0.738	0.498	0.584	NEW
0.000	0.000	0.000	0.000	0.000	0.485	0.047	CHURN
0.000	0.000	0.000	0.000	0.000	0.489	0.066	SHOPPER
0.000	0.000	0.000	0.000	0.000	0.498	0.248	UNCERTAIN
Weighted Avg. 0.585	0.585	0.342	0.585	0.432	0.496	0.413	

=== Confusion Matrix ===

```
   a   b   c   d   e   <-- classified as
   0  62   0   0   0 |   a = VALUABLE
   0 709   0   0   0 |   b = NEW
   0  58   0   0   0 |   c = CHURN
   0  82   0   0   0 |   d = SHOPPER
   0 301   0   0   0 |   e = UNCERTAIN
```

=== Run information ===

Scheme: weka.associations.Apriori -N 10 -T 0 -C 0.68 -D 0.05 -U 1.0 -M 0.1 -S -1.0 -c -1
Relation: mobile-banking-data-T
Instances: 1212
Attributes: 4
REGION
GENDER
AGE
CUSTOMERVALUE
=== Associator model (full training set) ===

Apriori
=======

Minimum support: 0.15 (182 instances)
Minimum metric <confidence>: 0.68
Number of cycles performed: 17

Generated sets of large itemsets:

Size of set of large itemsets L(1): 7

Size of set of large itemsets L(2): 15

Size of set of large itemsets L(3): 7

Best rules found:

1. AGE=ADULT CUSTOMERVALUE=NEW 278 ==> GENDER=Male 205 <conf:(0.74)> lift:(1.08) lev:(0.01) [14] conv:(1.18)
2. AGE=ADULT 458 ==> GENDER=Male 335 <conf:(0.73)> lift:(1.07) lev:(0.02) [21] conv:(1.16)
3. AGE=ADULT CUSTOMERVALUE=NEW 278 ==> REGION=NAIROBI 202 <conf:(0.73)> lift:(1.08) lev:(0.01) [14] conv:(1.18)
4. REGION=NAIROBI AGE=ADULT 322 ==> GENDER=Male 231 <conf:(0.72)> lift:(1.05) lev:(0.01) [10] conv:(1.1)
5. AGE=ADULT 458 ==> REGION=NAIROBI 322 <conf:(0.7)> lift:(1.04) lev:(0.01) [13] conv:(1.09)
6. CUSTOMERVALUE=NEW 709 ==> GENDER=Male 496 <conf:(0.7)> lift:(1.02) lev:(0.01) [10] conv:(1.04)
7. GENDER=Female 382 ==> REGION=NAIROBI 266 <conf:(0.7)> lift:(1.03) lev:(0.01) [8] conv:(1.07)
8. REGION=NAIROBI CUSTOMERVALUE=NEW 478 ==> GENDER=Male 332 <conf:(0.69)> lift:(1.01) lev:(0) [4] conv:(1.02)
9. CUSTOMERVALUE=UNCERTAIN 301 ==> REGION=NAIROBI 209 <conf:(0.69)> lift:(1.03) lev:(0.01) [6] conv:(1.06)
10. GENDER=Male AGE=ADULT 335 ==> REGION=NAIROBI 231 <conf:(0.69)> lift:(1.02) lev:(0) [5] conv:(1.04)

We therefore proposed FRAT – FRM approach which incorporates transaction type attribute. This is shown in figure 4.1

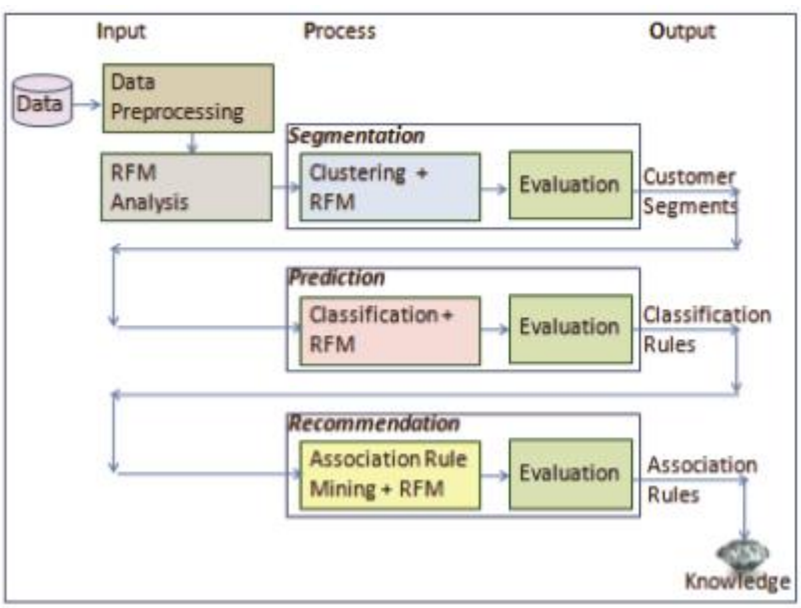


Figure 4.1 Proposed FRAT – FRM approach model

As indicated in figure 4.1 above the following describes the proposed approach

a) Step 1 Data pre-processing:

IPO **(Input, Process and Output)** diagram of the proposed model Dimensionality.

i. **Reduction:** Unnecessary attributes should are deleted, such as attributes that have only a few values (the others are null) or have only single value.
ii. **Filling:** Missing values should are filled in using an appropriate approach.
iii. **Handling:** Outliers and inaccurate values are handled and removed from the dataset.
iv. **Transformation:** Data should be transformed into an appropriate format.
v. **Discretization:** Before association rule mining task, continuous attributes should be encoded by discretizing the original values into a small number of value ranges. Because they have nearly a different value for every case; with such a high cardinality they provide little meaning to the association rule mining process. One common example of this phenomenon is the attribute that stores age values. The age attribute aregrouped into three ranges such as Youth (18 - 35), Adult (36-55) and senior (56+).
vi. **Concept Hierarchy Generation:** This method can be used to replace low level concepts by higher level concepts (such as CountiesMombasa, Nairobi, etc).

b) Step 2. RFM Analysis

In this step, FRAT - RFM analysis is applied by defining the scaling of F-R-A-T attributes. This process is divided into three parts introduced in the following:

i. Sort the data of four**F-R–A–T** attributes by descending or ascending order.
ii. Partition the three **F-R–A–T**attributes respectively into 5 equal parts and each part is equal to 20% of all. The five parts are assigned 5, 4, 3, 2 and 1 score that refer to the customer contributions. The '5' refers to the most customer contribution, while '1' refers to the least contribution to revenue.
iii. Repeat the previous sub-processes (i and ii) for each **F-R-A-T** attribute individually. There are total 625 (5 x 5 x 5 x 5) combinations since each attribute in **F-R-A-T** attributes has 5 scaling (5, 4, 3, 2 and 1).

The transaction done by the customers have different revenue elements, for instance Balance Enquiry Service has a flat fee while funds transfer is commission tiered as per the amount of money being transferred making the element of transaction type a very important attribute in this study.

The table below shows the segmentation of the customers according to Frequency, Recency, Amount (Monetary) and Transaction (T) before incorporating the attributes with those of the demographic features.

CLUSTER	FRAT - RATING	CUSTOMERVALUE
CLUSTER001	F↑R↑A↓T↑	VALUABLE
CLUSTER001	F↑R↓A↑T↑	VALUABLE
CLUSTER001	F↑R↑A↑T↑	VALUABLE
CLUSTER001	F↑R↑A↑T↓	VALUABLE
CLUSTER002	F↑R↓A↓T↑	UNCERTAIN
CLUSTER002	F↓R↓A↑T↑	UNCERTAIN
CLUSTER002	F↓R↓A↓T↓	UNCERTAIN
CLUSTER003	F↓R↑A↓T↓	NEW-INACTIVE
CLUSTER004	F↓R↑A↑T↓	SPENDER
CLUSTER004	F↓R↑A↑T↑	SPENDER
CLUSTER005	F↑R↑A↓T↓	NEW
CLUSTER005	F↓R↑A↓T↑	NEW
CLUSTER006	F↓R↓A↑T↓	CHURN
CLUSTER006	F↓R↓A↓T↑	CHURN
CLUSTER006	F↑R↓A↓T↓	CHURN

Table 4.1 FRAT segments above ↑ or below ↓ the average weight

Interpretation of table 4.1 above

Cluster01 shows the valuable customers with high values of F, R, A and T, all above average. These customers should be rewarded in one way or another for their loyalty to the business.

Cluster02 shows the uncertain whose behaviours are unpredictable. Most of them have Frequency Monetary and Recency below average

Cluster02 shows the New but inactive customers who registered recently but went inactive. All the values are below average except Recency.

Cluster04 represents spender customers. The R, A, are above average while the Frequecy, F, is below average. These customers are important to the business because of the revenue generated from them.

Cluster05 has new customers where Amount is low Recency and Transactions/Frequencyis below or above average. The new customers seem to be exploring multiple services with low monetary values.

Cluster06 shows churn customers who might have moved to the competitor. They only have Monetary score above average, the rest of the attributes are below are average.

4.0.4 Objective two results

The proposed study's objective two was to evaluate the effectiveness of the approach in segmentation and profiling of mobile banking customers approach by including transaction type as an attribute.

Objective two results are organized into 3 sections as shown in diagram 4.1 above

a) Input
b) Process
c) Output

Pre-processing results

a) Demographic Attributes

The data totalling to 1212 instances of active Mobile banking customers for the last from Jan 2015 to August 2017 derived from Nairobi, Mombasa, Nakuru, Eldoret and Kisumu regions were analysed.

A total of 426,908 were the active mobile banking customers within the period under study. From this number; 289,062 were from Nairobi region representing 68%, 55,748 from Mombasa region representing 13%, Nakuru and Eldoret had 7% each with 29,669 and 29,391 active mobile Banking customers respectively. Kisumu had the least active customers with 23,038 representing 6%.

The customer value parameters were divided into six groups for segmentation and profiling.

mobile-banking-data.csv   mobile-banking-data.arff   Data-collection-authorization.pdf

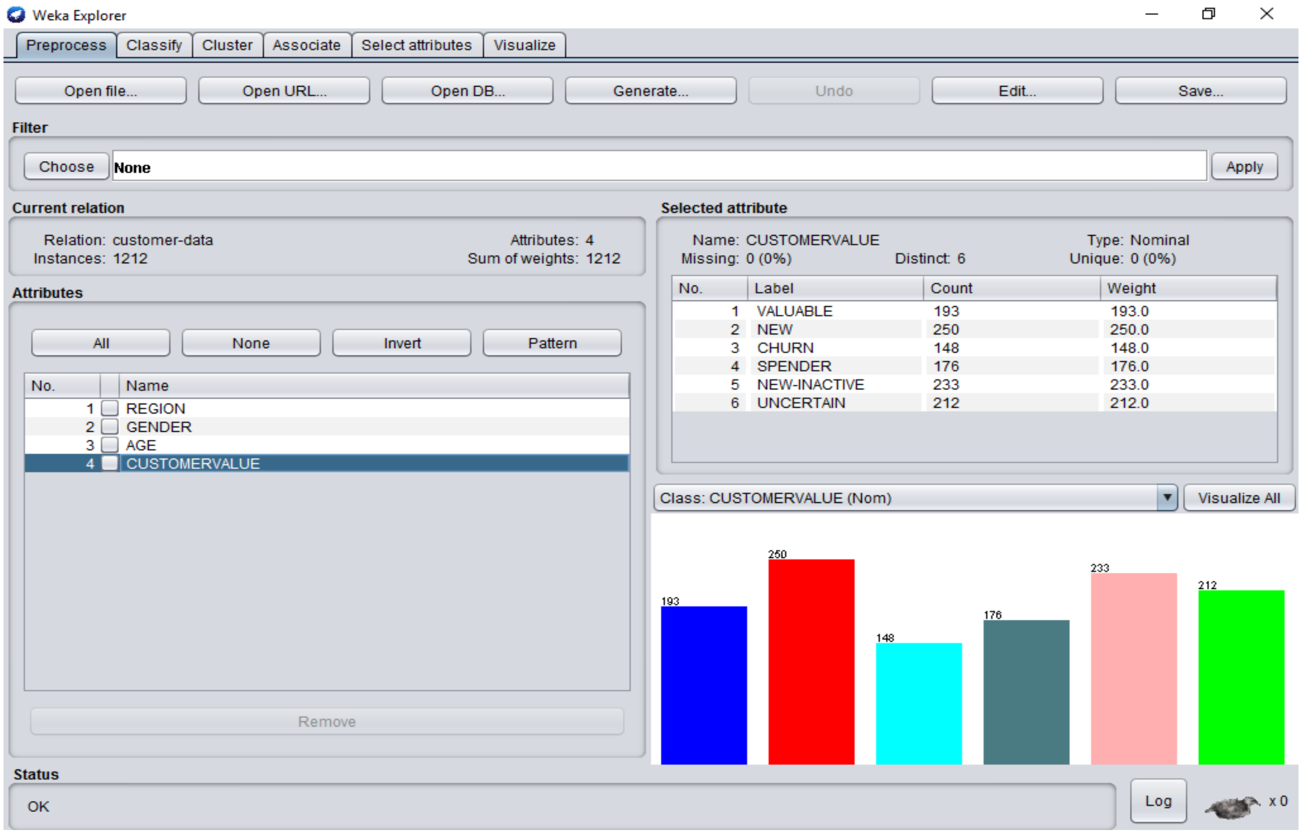


Figure 4.2 Weka pre-processing

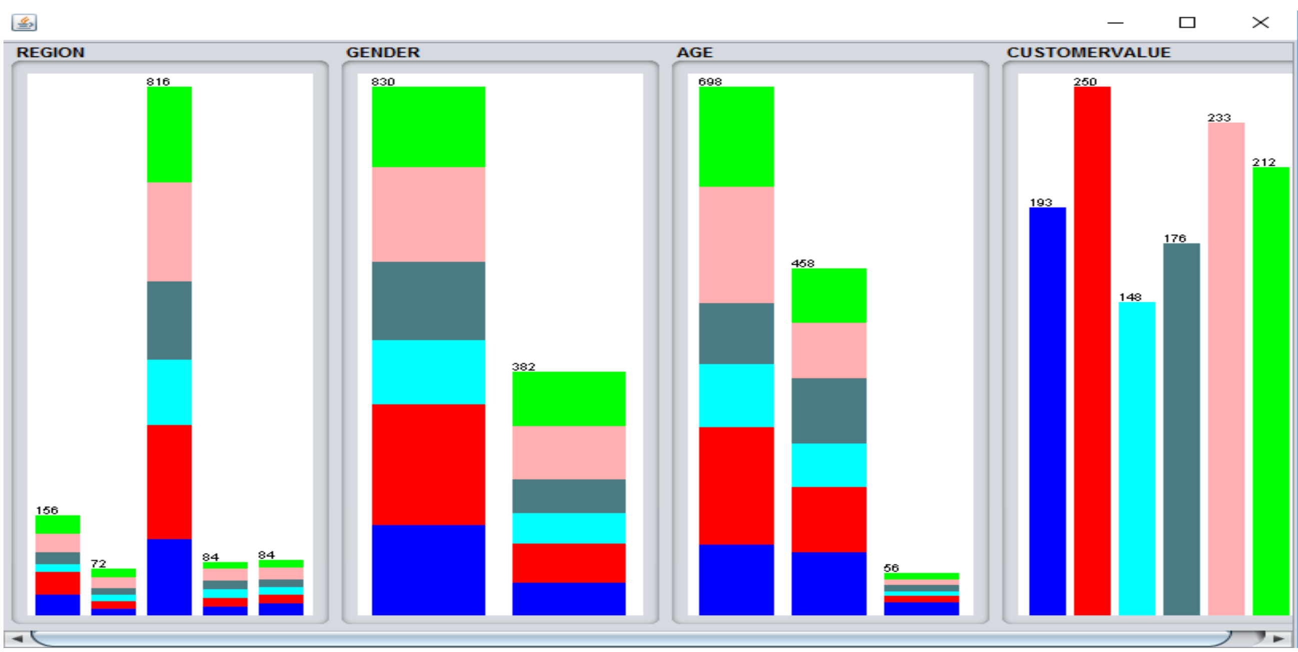


Figure 4.3 Visualization of all the attributes

b) RFM Analysis

In this step, FRAT - RFM analysis is applied by defining the scaling of F-R-A-T attributes. This process is divided into four parts introduced in the following:

i. Sort the data of four F-R–A–T attributes by descending or ascending order.
ii. Partition the three F-R–A–T attributes respectively into 5 equal parts and each part is equal to 20% of all. The five parts are assigned 5, 4, 3, 2 and 1 score that refer to the customer contributions. The '5' refers to the most customer contribution, while '1' refers to the least contribution to revenue.
iii. Repeat the previous sub-processes (i and ii) for each F-R-A-T attribute individually. There are total 125 (5 x 5 x 5 x 5) combinations since each attribute in F-R-A-T attributes has 5 scaling (5, 4, 3, 2 and 1).

The transaction done by the customers have different revenue elements, for instance Balance Enquiry Service has a flat fee while funds transfer is commission tiered as per the amount of money being transferred making the element of transaction type a very important attribute in this study.

Classification Results

Data classification using J48 classification algorithm

Attributes Classification using J48 algorithm and percentage split of 66% (66% training data, 34% test data) and location as the class attribute for more accurate results.

i. **Classification:** Using customer demographic variables and FRAT (R–F–M) attributes, classification rules are discovered by C4.5 Decision Tree algorithm. In data analysis techniques, the capabilities of C4.5 for classifying large datasets have already been confirmed in many studies. C4.5 algorithm first grows an initial tree using the divide-and-conquer strategy and then prunes the tree to avoid over-fitting problem. It calculates overall entropy and information gains of all attributes. The attribute with the highest information gain is chosen to make the decision. So, at each node of tree, C4.5 chooses one attribute that most effectively splits the training data into subsets with the best cut point, according to the entropy and information gain. Let D be a dataset expressed in terms of p attributes from the set A = {Al, A2,...,Ap}, and k classes from the set C = (Cl, C2,..., Ck}. Thus each sample d

∈D has p+1 tuples d = <V1, V2,.., Vp; Cj>, where Vi ∈ Range(Ai) is a value in the range of the attribute Ai ∈ A and Cj ∈ C.

A decision tree is constructed using C4.5 algorithm that selects an attribute Ai and a subset of its values Vi to branch on.

ii. **Evaluation of Classification Accuracy:** Commonly used validation techniques for classification are simple validation, cross validation, n-fold cross validation, percentage split and bootstrap method. In our model, we propose n-fold cross validation technique where n=12 because it matters less how the data gets divided. In this technique, dataset is divided into n subsets and the method is repeated n times. Each time, one of the n subsets is used as the test set and the other n-1 subsets are put together to form a training set. Then the average error across all n trials is computed.

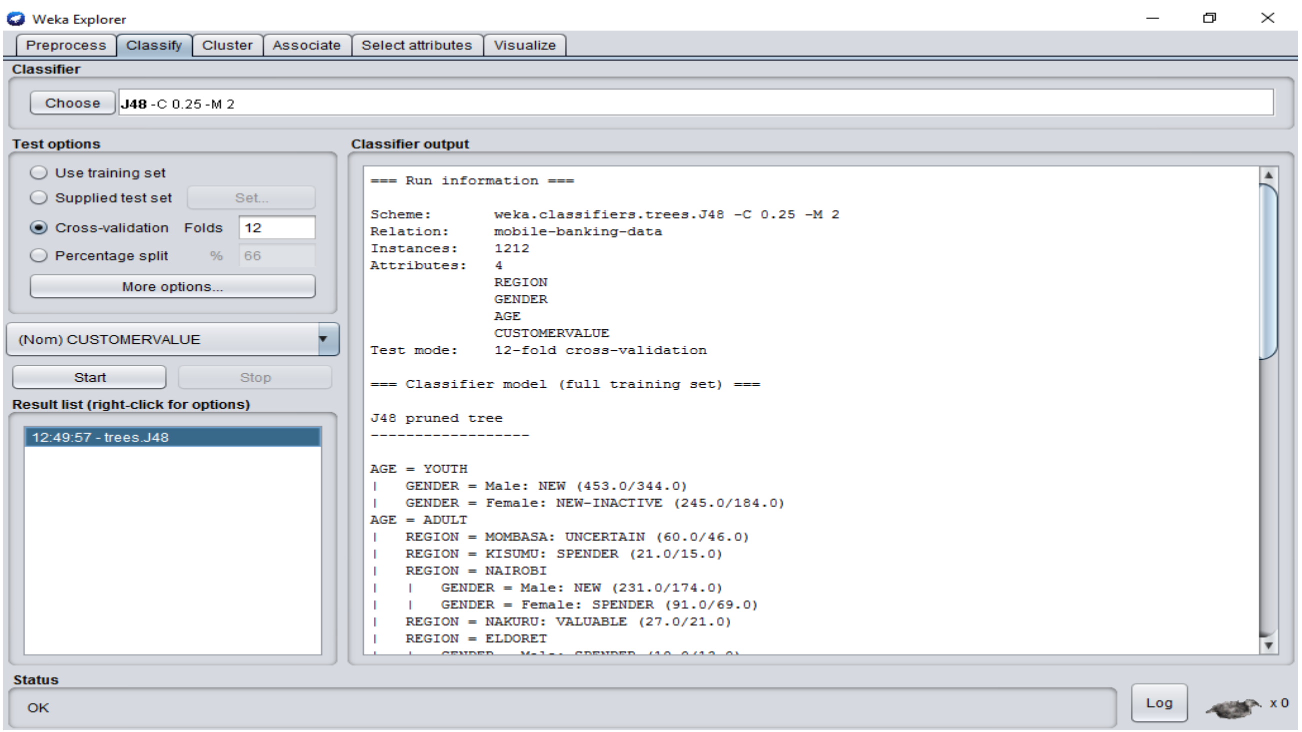


Figure 4.3a Classification Results

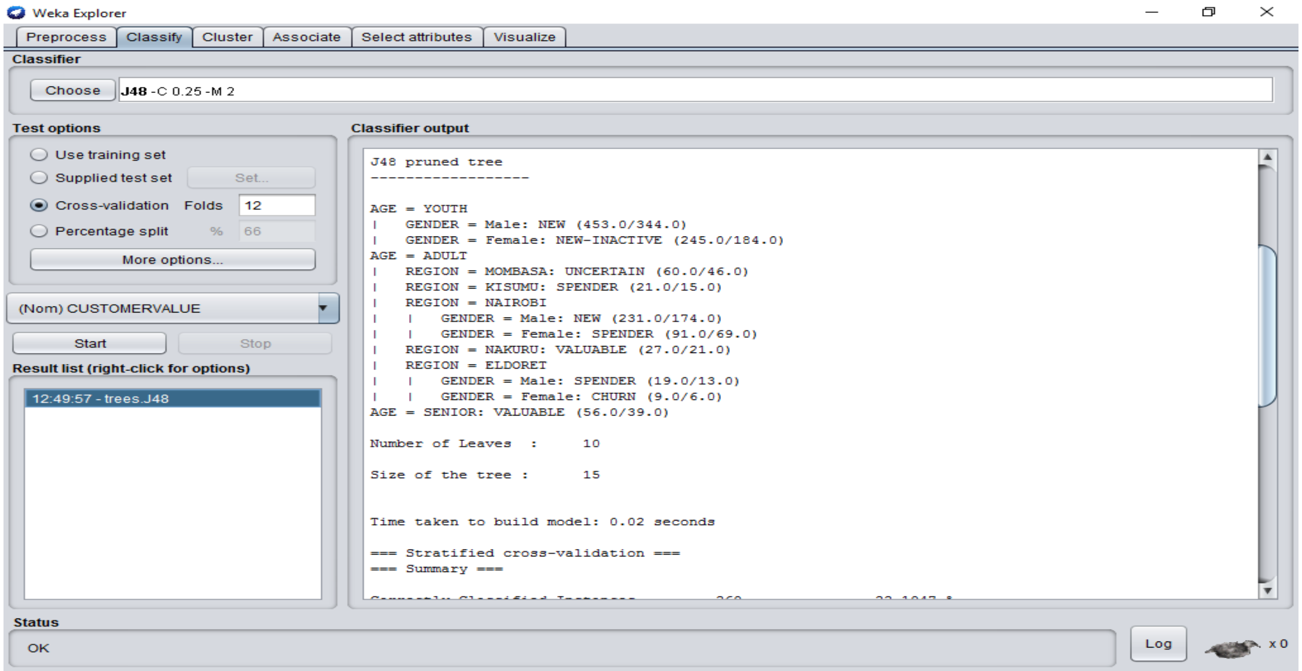


Figure 4.3b Classification Results

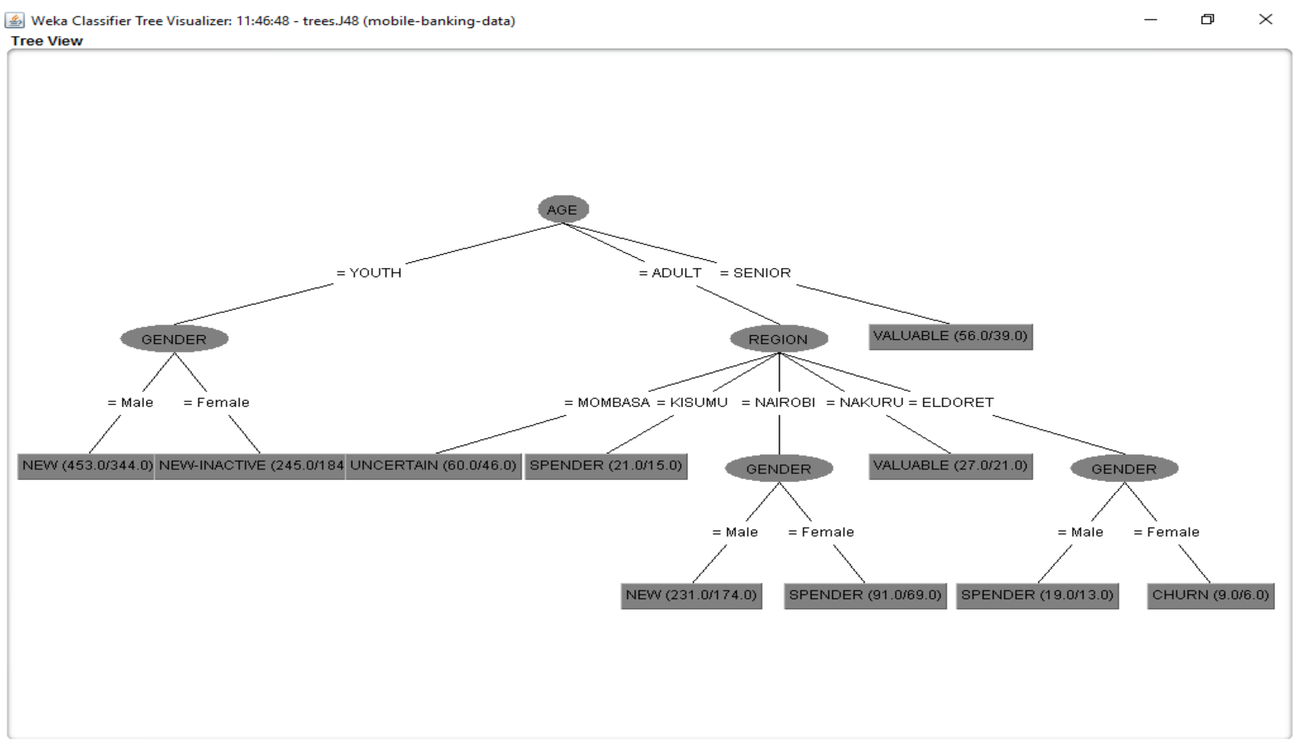


Figure 4.4Model Visualization Results – Decision tree

Interpretation of the Rules generated by J48 algorithm as per the study

The output of the classification algorithm as indicated in figures 4.3a, 4.3b and 4.4 above were interpreted as below to assist marketers and or management make relevant decisions.

Sample rules derived from the J48 algorithm

i. Many of the new mobile banking customers are male youth customers.
ii. Most of the New Inactive mobile banking customers are female youth
iii. Majority of adult mobile banking customers from Mombasa region are uncertain
iv. Many spender mobile banking customers from Kisumu are adults.
v. Many of Adult New Nairobi Mobile Banking customers are male.
vi. Female Adult mobile banking customers from Nairobi region are Spender customers.
vii. Majority of Adult Nakuru Customers are loyal customers.
viii. Most of the Senior Mobile Banking Customers are loyal customers.
ix. Male Adult Eldoret Customers are spender customers
x. Most of the Female Eldoret Mobile Banking Customers are churn customers projected in figure 4.4 above

=== Detailed Accuracy By Class ===

	TP-Rate	**FP-Rate**	**Precision**	**Recall**	**F-Measure**	**ROC-Area**	**PRC-Area**	**Class**
	0.088	0.076	0.181	0.088	0.118	0.529	0.176	VALUABLE
	0.644	0.525	0.242	0.644	0.352	0.521	0.208	NEW
	0.014	0.012	0.133	0.014	0.025	0.402	0.102	CHURN
	0.176	0.099	0.231	0.176	0.200	0.552	0.172	SPENDER
	0.215	0.175	0.226	0.215	0.220	0.517	0.197	NEW-INACTIVE
	0.038	0.074	0.098	0.038	0.054	0.510	0.174	UNCERTAIN
Weighted Avg.	0.222	0.183	0.189	0.222	0.175	0.509	0.177	

=== Confusion Matrix ===

```
  a   b   c   d   e   f <-- classified as
17 103   5  23  29  16 |  a = VALUABLE
16 161   0  17  36  20|  b = NEW
13  79   2  17  29   8  |   c = CHURN
17  93   3  31  22  10  |   d = SPENDER
```

12 125   4 22 50 20 | e = NEW-INACTIVE
19 105   1 24 55   8 | f = UNCERTAIN

Association Results

Generation of Association Rules using Apriori algorithm and Confidence, Lift, Leverage and Conviction of 68%

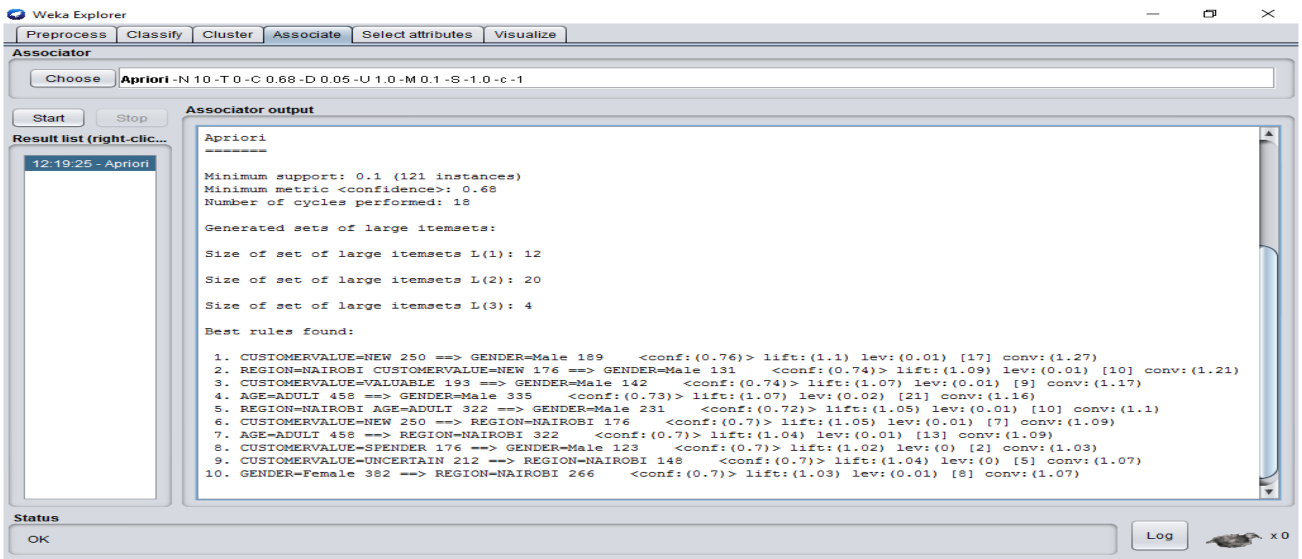


Figure 4.5: Association Rule Mining

i. The best association rule with 76% Certainty was that the majority of new customers were male customers.
ii. The second Rule with 74% certainty was that most male new mobile banking customers are in Nairobi region.
iii. The third best rule with 74% Certainty was that majority of loyal Mobile Banking Customers were male.
iv. With 73% Certainty, the model shows that majority of Adult Mobile Banking Customers are Male

4.0.5 Study Findings for Customer Behavior

Class implementing an Apriori-type algorithm that iteratively reduces the minimum support until it finds the required number of rules with the given minimum confidence. It is a Fast Algorithm for Mining Association Rules in Large Databases hence was used in this study.

In addition, the algorithm has an option to mine class best association rules for profiling of the data under study.

A customer segment is not as enough to identify, and then to predict customer's behavior. Many direct marketers believe that the RFM variables of customers are generally associated with customer profiling. For example, customers with profiles age = youth and gender = male are generally new customers, while customers with profiles age = adult, Gender = Female and location = Nairobi are generally spender customers. The classification rules were discovered using demographic variables (age, gender, location) and FRAT-RFM values of customer segments.

4.0.6 Prediction

In this step, classification rules are discovered using demographic variables (age, gender, location etc.) and RFM values of customer segments to predict future customer behaviors. For example, if age = youth and gender = male and Region = MOMBASA then R↑F↑M↓T↓, where the sign ↑ denotes that the value is greater than an average and sign ↓ denotes that the value is smaller than an average. The rationale of this step is that if customers have similar demographic values, then they are very likely also to have similar RFM values. In fiercely competitive environments, discovering classification rules using customer demographic values is important for helping decision makers to target customer profiles more clearly. Additionally, the effect of classification rules on recommendations should be investigated to make more effective marketing strategies. The detail process of this stage is expressed into two sub-steps.

- **Classification:** Using customer demographic variables and F-R-A-Tattributes, classification rules are discovered by C4.5 Decision Tree (Quinlan, 2014) algorithm. In data analysis techniques, the capabilities of C4.5 for classifying large datasets have already been confirmed in many studies. C4.5 algorithm first grows an initial tree using the divide-and-conquer strategy and then prunes the tree to avoid overfitting problem. It calculates overall entropy and information gains of all attributes. The attribute with the highest information gain is chosen to make the decision. So, at each node of tree, C4.5 chooses one attribute that most effectively splits the training data into subsets with the best cut point, according to the entropy and information gain. Let D be a dataset expressed in terms of p attributes from the set A = {Al, A2,...,Ap}, and k classes from the set C = (Cl, C2,..., Ck}. Thus each sample d ∈ D has p+1 tuples d = <V1, V2,.., Vp; Cj>, where Vi ∈ Range(Ai) is a value in the range of the attribute Ai ∈ A and Cj ∈ C. A decision tree is constructed using C4.5 algorithm that selects an attribute Ai and a subset of its values Vi to branch on.

- **Evaluation of Classification Accuracy:** Commonly used validation techniques for classification are simple validation, cross validation, n-fold cross validation, percentage split and bootstrap method. In the model, we propose n-fold cross validation technique where n=12 because it matters less how the data gets divided. In this technique, dataset is divided into n subsets and the method is repeated n times. Each time, one of the n subsets is used as the test set and the other n-1 subsets are put together to form a training set. Then the average error across all n trials is computed.
- **Rules:** ARM algorithms use support and confidence thresholds and usually produce a large number of association rules which may not be interesting. An association rule is valid if it satisfies some evaluation measures. Evaluation process is needed to handle a measure in order to evaluate its interestingness. In my approach, I propose to evaluate interestingness of mined rules and to express the relevance of rules with two descriptive criteria: Lift and Loevinger. These two criteria are defined on itemsets X, Y and rule R: X å Y as follows:

$$\text{Lift}(R) = \frac{P(XY)}{P(X)P(Y)} \qquad (1)$$

$$\text{Loevinger(R)} = 1 - \frac{P(X)P(\text{-}Y)}{P(X\text{ - }Y)} \qquad (2)$$

Lift criterion represents the probability scale coefficient of having Y when X occurs. Loevinger criterion normalizes the centered confidence of a rule according to the probability of not satisfying its consequent part Y. In general, greater Lift and Loevinger values indicate stronger associations.

4.0.7 Discussion of Results

By analyzing the profiles of the mobile Banking customers, the marketing and the management by extension can concentrate on a market segment which generates more revenue.

The study proposes a novel three-step approach which uses FRAT-RFM analysis in three data mining tasks: clustering, classification and association rule mining, applied one after another. **Firstly**, customer segments with similar FRAT- RFM values are identified to be able to adopt different marketing strategies for different customer segments. **Secondly**, classification rules are discovered using demographic variables (age, gender and location) and FRAT- RFM values of customer segments to predict future customer behaviors and to target customer profiles more clearly. **Thirdly**, association rules are discovered to identify the associations between customer segments, customer profiles and service items purchased, and therefore to recommend products with associated rankings, which results in better customer satisfaction and cross selling.

Below is the Classification and Association output done using J48 and apriori algorithms respectively to compare the data processing, segmentation and profiling without the transaction type using cross validation with n=12

From this we have established that all of the class attributes had zero accuracy parameters except NEW customer value class attribute for the classification rule as opposed to when the transaction type was introduced. The tree also generated only one leaf when CUSTOMERVALUE class is used as the class in the model. In the association rule for the same data, the best rule had 74% certainty as opposed to the 76% certainty achieved by including transaction type where Minimum Confidence is set to 68% for both.

Below is the output of the processing of Data using classification and association algorithms respectively on Weka

=== Run information ===

Scheme: weka.classifiers.trees.J48 -C 0.25 -M 2
Relation: mobile-banking-data-T
Instances: 1212
Attributes: 4
REGION
GENDER
AGE
CUSTOMERVALUE
Test mode: 12-fold cross-validation

=== Classifier model (full training set) ===

J48 pruned tree

: NEW (1212.0/503.0)

Number of Leaves: 1

Size of the tree: 1

Time taken to build model: 0.01 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances	709	58.4983 %
Incorrectly Classified Instances	503	41.5017 %
Kappa statistic	0	
Mean absolute error	0.2347	
Root mean squared error	0.3425	
Relative absolute error	99.8373 %	
Root relative squared error	99.9996 %	
Total Number of Instances	1212	

=== Detailed Accuracy By Class ===

TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area	PRC Area	Class
0.000	0.000	0.000	0.000	0.000	0.486	0.050	VALUABLE
1.000	1.000	0.585	1.000	0.738	0.498	0.584	NEW
0.000	0.000	0.000	0.000	0.000	0.485	0.047	CHURN
0.000	0.000	0.000	0.000	0.000	0.489	0.066	SHOPPER
0.000	0.000	0.000	0.000	0.000	0.498	0.248	UNCERTAIN
Weighted Avg. 0.585	0.585	0.342	0.585	0.432	0.496	0.413	

=== Confusion Matrix ===

```
  a   b   c   d   e   <-- classified as
  0  62   0   0   0 |   a = VALUABLE
  0 709   0   0   0 |   b = NEW
  0  58   0   0   0 |   c = CHURN
  0  82   0   0   0 |   d = SHOPPER
  0 301   0   0   0 |   e = UNCERTAIN
```

=== Run information ===

Scheme: weka.associations.Apriori -N 10 -T 0 -C 0.68 -D 0.05 -U 1.0 -M 0.1 -S -1.0 -c -1
Relation: mobile-banking-data-T
Instances: 1212
Attributes: 4
REGION
GENDER
AGE
CUSTOMERVALUE
=== Associator model (full training set) ===

Apriori
=======

Minimum support: 0.15 (182 instances)
Minimum metric <confidence>: 0.68
Number of cycles performed: 17

Generated sets of large itemsets:

Size of set of large itemsets L(1): 7

Size of set of large itemsets L(2): 15

Size of set of large itemsets L(3): 7

Best rules found:

1. AGE=ADULT CUSTOMERVALUE=NEW 278 ==> GENDER=Male 205 <conf:(0.74)> lift:(1.08) lev:(0.01) [14] conv:(1.18)
2. AGE=ADULT 458 ==> GENDER=Male 335 <conf:(0.73)> lift:(1.07) lev:(0.02) [21] conv:(1.16)
3. AGE=ADULT CUSTOMERVALUE=NEW 278 ==> REGION=NAIROBI 202 <conf:(0.73)> lift:(1.08) lev:(0.01) [14] conv:(1.18)
4. REGION=NAIROBI AGE=ADULT 322 ==> GENDER=Male 231 <conf:(0.72)> lift:(1.05) lev:(0.01) [10] conv:(1.1)
5. AGE=ADULT 458 ==> REGION=NAIROBI 322 <conf:(0.7)> lift:(1.04) lev:(0.01) [13] conv:(1.09)
6. CUSTOMERVALUE=NEW 709 ==> GENDER=Male 496 <conf:(0.7)> lift:(1.02) lev:(0.01) [10] conv:(1.04)
7. GENDER=Female 382 ==> REGION=NAIROBI 266 <conf:(0.7)> lift:(1.03) lev:(0.01) [8] conv:(1.07)
8. REGION=NAIROBI CUSTOMERVALUE=NEW 478 ==> GENDER=Male 332 <conf:(0.69)> lift:(1.01) lev:(0) [4] conv:(1.02)
9. CUSTOMERVALUE=UNCERTAIN 301 ==> REGION=NAIROBI 209 <conf:(0.69)> lift:(1.03) lev:(0.01) [6] conv:(1.06)
10. GENDER=Male AGE=ADULT 335 ==> REGION=NAIROBI 231 <conf:(0.69)> lift:(1.02) lev:(0) [5] conv:(1.04)

The second objective of this study was to evaluate the effectiveness of the approach in segmentation and profiling of mobile banking customers.

Findings from FRAT (RFM) approaches were divided into two categories, that is, Classification Results and Association Rule mining results. These were obtained by adding Transaction Type attribute to the Frequency, Recency and Monetary features as well as demographic attributes.

From the study, we can learn that the transaction type forms an important attribute while doing segmentation and profiling of customers. The models reviewed did not take into consideration this attribute hence Segmentation and profiling had not covered 360 Degrees behavior of the customer.

The algorithms used, J48 Algorithm - Association and Apriori Algorithm – Classification, present a novel picture of the best rules while adjusting Apriori Algorithm rule properties of Confidence, Conviction, Leverage and Lift until the best rules are achieved.

CHAPTER FIVE

5.0.1 Introduction

This chapter provided the summary of the findings from Chapter Four, Conclusions and Recommendations of the study based on the objectives of the study. It was a very crucial chapter as it would make summary of the whole research, conclude and make recommendations. The objectives of this study were: To establish the appropriate approach for mobile banking customers' segmentation and profiling by the use of customer FRAT-RFM and demographic variables; To evaluate the effectiveness of the approach in segmentation and profiling of mobile banking customers.

5.0.2 Conclusion

A comprehensive customer segmentation method would be used in customer acquisition as well as customer retention and development. Churn avoidance, complaint management, one to one marketing etc. would be so more accurate with thorough customer segmentation. Besides, an effective customer profiling will complement the customer segmentation in order to design marketing strategies.

To achieve comprehensive customer segmentation and customer profiling, input variables and their sequence, segment's evaluation and their visualization are so important. LTV, RFM and demographic variables are the most popular marketing variables amongst both academics and practitioners.

While these variables were used by many authors, there is a lack of clustering methods considering all of these variables and transaction type attribute. In this study, a comprehensive method for customer segmentation and profiling was proposed based on Demographic and FRAT- RFM variables. The novelties of this study could be viewed from three perspectives. First, it reveals that different sequences of involving FRAT - RFM and demographic variables in clustering should be examined to achieve the most suitable one for the segmentation process. However, it may vary regarding the characteristics of different studies.

It could be inferred about this data that in Financial Institutions while segmenting customers, FRAT - RFM features should be used before demographic features. FRAT- RFM features will play more important role in identifying chief segments when they are used first. Second, due to importance of Life Time Value in all stages of CRM, in this study the appropriate framework was chosen based on the Life Time Value dispersion quality. In other words, the selected framework was able to differentiate clusters better amongst the other frameworks regarding their Life Time Values. Third, the innovative rank based visualization method in this study resulted in more meaningful profiles. Designing different marketing plans would be facilitated when the comparison is based on the proposed rank based profiling. This study had also very interesting implications for the target business.

Finally from the study, we have established that all of the class attributes had zero accuracy parameters except NEW customer value class attribute for the classification rule as opposed to when the transaction type was introduced. The tree also generated only one leaf when CUSTOMERVALUE class is used as the class in the model. In the association rule for the same data, the best rule had 74% certainty as opposed to the 76% certainty achieved by including transaction type where Minimum Confidence is set to 68% for both.

This therefore explains the improvement on the certainty of the approach when transaction type is included as an attribute.

5.0.3 Recommendations for Future Research

Future research can focus in the followings: First, the proposed approach can be tested for other versions of RFM such as Weighted RFM (WRFM), Timely RFM (TRFM). As the number of additional variables increases, the number of cells will geometrically increase. For example, if we add two types of product parameter, the number of FRAT cells becomes $2 \times 5 \times 5 \times 5 = 500$. Thus, it is unrealistic to estimate RFM model with more than two additional variables.

Secondly, the effectiveness of the proposed approach can be evaluated for different application domains such as for comparing the segments of data from different banks using “Supplied Test Set” Data Option of Data Mining Tools eg Weka.

5.0.4 Contributions

The study can easily contribute in the Development of expert system/knowledge-based systems to help management to select and manage the portfolio of segments. Such systems would ideally be incorporated in an effective Decision Support Systems (DSS). The key to this is the development of a set of rules summarizing our current understanding of market segmentation and profiling. These rules can reflect the empirical generalizations in this area and can be aided by appropriate meta-analyses. In addition, more thought needs to be given to the psychological and other impediments to use and implementation of the model by including transaction type as an attribute.

References

Al-Ajam and Khatil. (2013). Technology Acceptance Model.

Birant et al... (2011). Data Mining Using RFM Analysis, Knowledge-Oriented Applications in Data Mining,. *Prof. Kimito Funatsu (Ed.), ISBN: 978-953-307-154-1, InTech*, http://www.intechopen.com/books/knowledge-oriented-applications-in-data-mining/data-mining-using-rfmanalysis.

C. H. Wu, S. C. (2011). Targeting Customers via Discovery Knowledge for the Insurance Industry. *Expert System with Application*, pp. 291-299.

CBK. (2015). *Bank Supervision Annual Report 2015.* Central Bank of Kenya.

Chuang, H. &. (2012). A study on the applications of data mining techniques to enhance customer lifetime value – based on the department store industry. *Proceedings of the 9th International Conference on Machine Learning and Cybernetics*, pp. 168-173, ISBN: 978-1424420964, Kunming, China, July 2010, IEEE.

Cockrum, J. (2011). 101 Powerful Marketing Strategies for Growing Your Business Now!,. *SmallBiz Marketing Services*, pp. 24-27.

Co-opBank. (2017). *Co-operative Bank (k) Limited*. Retrieved from www.co-opbank.co.ke.

Erdem Tulin, K. K. (2016). Size and share of customer wallet. *International Journal of Research in Marketing*, Volume 33, Issue 1, Pages 1-240 .

Everett Rogers. (2011). *Diffusion of Innovations, 5th Edition.*

Fatemeh A. K. Et al. (2014). A Hybrid Segmentation Approach for Customer Value. *INTERDISCIPLINARY JOURNAL OF CONTEMPORARY RESEARCH IN BUSINESS OCT 2014*, pages 144-150.

Hosseini, S., & Maleki, A. &. (2011). Cluster analysis using data mining approach to develop CRM methodology to assess the customer loyalty, Expert Systems with Applications,. Vol. 37, No. 7, (July 2010) 5259–5264, ISSN:09574174.

Hujun Yin, E. a. (2014). Intelligent Data Engineering and Automated Learning -- IDEAL 2014. *15th International Conference, Salamanca Spain 10-12 2014*.

Jerry Fjermestad, . C. (2015). Enabling and Measuring Electronic Customer Relationship Management Readines. *Electronic Customer Relationship Management*.

Johnson et al, M. G. (2015). The evolution and future of national customer satisfaction index models. *International Journal of Business Quantitative Economics and Applied Management Research*, Vol. 2, No. 5 (15 October 2015): pp. 56-71. .

Kurt Ruf, . D. (2013). Contemporary database marketing: Concepts and applications. *Evanston: Racom Communications*.

Lee In. (2016). The Impact of Mobile Payments on the Success and Growth of Micro-Business. *Encyclopedia of E-Commerce Development, Implementation, and Management, Volume 1*.

Ling & Yen. (2011). Customer Relationship Management: An Analysis Framework and Implementation. *Journal of Computer Information Systems*, Vol. 41, No. 3, 2011, pp. 82-97.

M. Namvar et al. (2011). An approach to optimised customer segmentation and profiling using RFM, LTV, and demographic features. *Int. J. Electronic Customer Relationship Management,*, Vol. 5, Nos. 3/4, 2011.

Michael Hennessy, M. F. (2012). Advancing Reasoned Action Theory.

Mo Et al, J. K. (2011). A two-stage clustering approach for multi-region segmentation. *Expert Systems with Applications*, Vol. 37, No. 10, pp.7120–7131.

Mohsen Alvandi et al... (2012). K-Mean Clustering Method For Analysis Customer. *International Research Journal of Applied and Basic Sciences* , Vol, 3 (11): 2294-2302.

Namwar et al. (2011). 'An approach to optimised customer segmentation and profiling using RFM, LTV, and demographic features. *Int. J. Electronic Customer Relationship Management*, Vol. 5, Nos. 3/4, pp.220–235. .

Quinlan, J. R. (2014). C4.5 Programs for Machine Learning. *Morgan Kaufmann Publishers.*, 302 pages.

Safeena, & Uduji. (2010;2013). Information Technology for Service delivery.

Sheth, A. P. (2011). Customer Relationship Management: Emerging Practice, Process, and Discipline. *Journal of Economic & Social Research*, Vol. 3, No. 2, 2010, pp. 1-34. .

Sim, e. a. (2011). Benefits of mobile Banking in compariison to non-mobile banking channels.

V. Vijayakumar, V. N. (2016). Applying RFM model and K-Means method in customer value analysis of an outfitter. *Proceedings of the 3rd International Symposium on Big Data and Cloud computing Challenges*, ISSN: 1865-5440, Part 12, pp. 665-672, ISBN:978-1848827615, Springer London.

www.edu.tech.wiki.com. (n.d.).

Yin, R. K. (2014). *Case study research: Design and methods. Los Angeles, CA: Sage.* Los Angeles.

Yin, R. K. (2014). *Case Study Research:Design and Methods.* CA: Thousands Oaks.

Young Sung Cho et al ... (2013). Incremental Weighted Mining based on RFM Analysis for Recommending Prediction in u-Commerce. *International Journal of Smart Home*, pp.133-144.

6.0 APPENDICES

6.0.1 APPENDIX A: TIMELINES

Project Timelines		
Activity Description	**Start**	**Finish**
Proposal drafting	Nov 2016	Jan 2017
Proposal presentation	Jan 2017	Feb 2017
Supervisors Allocation	Feb 2017	Feb 2017
Literature review	Feb 2017	May 2017
Data analysis	May 2017	September 2017
Project Defense - Final Dissertation	September 2017	October 2017
Report Submission	November 2017	

Table 5: Timelines

6.0.2 APPENDIX B: PROJECT BUDGET

Project Budget		
Description	**Unit Cost (KES)**	**Total cost (KES)**
2 Rims of printing papers	@1000	2000
Printing cost (6 copies of thesis document)	@1000	6000
Binding cost of 6 copies of document	@400	2400
Internet cost	@3000	3000
Total Cost		13,400

Table 6: Budget