Customer Perception and Responsiveness Behavior Study on Bulk SMS Advertisements for Target Customer Identification: The case of Ethio Telecom

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Declaration of originality

I, the undersigned, declare that this thesis and the work presented in it are my own and has been generated by me as the result of my own original research. I truly acknowledged and referred every material which used in this thesis work.

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Name Signature

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Thesis on

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By: **Samuel Getachew**

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ABSTRACT

Bulk-messaging, one of the technologies carried by the telecom industry, is a process of sending a large number of messages to many people at once. It is likely a more economical and effective way of marketing media as compared to others. Therefore, many companies are using this service for advertisement. Since it is most likely flooding without customers' consent, it can be one of the services that affect customers' responsiveness behavior. Studying customers' preferences prior to sending a message will help to overcome resource dissipation due to messaging and reduces customers' offensiveness.

The aim of this thesis is to identify factors that affect customers' responsiveness attitude and classify customers based on the level of responses, towards bulk-messaging advertisements in the case of Ethio Telecom customers. In this thesis, two different types of data were used i.e. data collected in-person via questionnaire and a Call Detail Records (CDR) data. Among 620 distributed questionnaires 528 were replied. Moreover, a CDR data of 29,506 messages got responses among 419,249 delivered messages. A statistical mean method and data mining techniques were used to classify a survey and CDR data respectively.

As a finding, all scale factors do have a significant influence on the responsiveness behavior of customers towards bulk-messaging except informativeness and relevancy. Furthermore, customers were classified into three levels i.e. a high-level, medium level, and low-level responsive customers with percentage responses of 16%, 44%, and 40% of the total respectively. Additionally, an entertaining type of advertisement has got more responses than others. The experiment result of both data set shows a good level of agreement. Finally, the thesis recommended that

all senders should give attention to care for customers' preferences towards any promoting services.

KEYWORDS

Bulk-SMS advertisement, Responsiveness, CDR, Classification, Survey data:

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ACRONYMS

ANN	Artificial Neural Network
CBS	Credit and Billing System
CDR	Call Detail Record
FNR	False Negative Rate
FPR	False Positive Rate
HLR	High Level Responsive Customers
K-NN	K-nearest neighbor
LLR	Low Level Responsive Customers
MLP	Multi-Layer Perceptron
MLR	Medium Level Responsive Customers
MMS	Multimedia System
RMSE	Root Mean Square Error
ROC	Receiver Operator Characteristic
SC	Short Code Number
SMS	Short Message Service
TNR	True Negative Rate
TPR	True Positive Rate
VAS	Value Added Service

1

INTRODUCTION

1.1 BACKGROUND

The development of telecoms' industry has brought an intensive use of telecommunication devices throughout the world. For instance, a smartphone is one of the devices used to make and receive a call, message and browse the internet almost from everywhere. According to Global System Mobile for Communication(GSM) Association released reports in June 2019, the number of active mobile subscribers in the world has reached 5.13 Billion [1]. In addition to this internet-enabled mobile phone has increased rapidly in the markets, and firms began to send news, alerts, and location-sensitive advertising to mobile users had started since.

As per "Infographics", which is an international bulk-SMS provider reports, SMS plays a role in the improvement of every business to communicate with its valuable customers. Approximately 66 percent of the total population of the world are using SMS service for business communication in the year 2018. The number is almost doubled in the last five years; which is 500 million messages sent per day that is around 182 billion in a year globally [2]. This report shows how SMS increasing and its adoption of advertisement is growing fast.

In conjunction with the personal nature of mobile phones, the use of SMS for marketing purposes has considerably increased in many parts of the world. Companies around the world take a chance to improve direct relations and reach each customer at an individual level. They follow the technologies and modify their advertisements to group customers' needs and attract their attention. Therefore, mobile phones turn out to be an important channel for advertising [3].

Bulk SMS is a process of sending many SMS messages to a large group of people at once. It is a fast way for conveying information within groups to several members, just within seconds. Bulk SMS can be considered as one of the most economical & effective ways of marketing as compared to any other mediums [4]. Therefore, bulk SMS advertising will help enterprises, banks, media companies and so on. Every mobile phone has a messaging application and its' global reachability of SMS is exceptionally high. Due to these advantages' enterprise companies are using bulk SMS advertisements for their marketing communication tools [4].

Customers' perception and responsiveness are the key points that are going to be assessed throughout this study. According to [5], customer perception is a customers' impression, awareness or consciousness about a company, or it offered. Typically, customer perception and responsiveness can be affected by advertising, reviews, social media, personal experiences, and others. In addition to these, it might be affected by different scale factors such as entertainment, informativeness, irritation, credibility, demography, relevancy, privacy and permission.

Ethio Telecom, which provides telecommunication services like voice, SMS and data services across Ethiopia, is a monopolized telecom service operator. Among all the provided services, bulk messaging is simple and cheap compared with other communication media in the country, and enterprises are preferring to use this service for marketing promotion demands.

Therefore, this study is mainly focused on the assessment of customer perception and responsiveness behavior towards bulk SMS advertising. Furthermore, it conducts a classification model based on the customer responsiveness to the service, specifically for Addis Ababa citizens. As per a data generated from mobile switching system, the average number of active mobile subscribers, that access the network each day is 4.69 million among Addis Ababa customers. Different companies found in the city are using the services to reach their customers directly to gain attention for their services. Due to these, customers are exposed to receive too many messages in a day. Unfortunately, most of the messages are considered as irrelevant by recipients, because target recipients were not defined. Which means the right message is not delivered to the right recipients.

1.2 PROBLEM STATEMENT

Ethio Telecom has around 60 million customers and serves them in different services. As per the data found from operators' internal documents, the number of mobile subscribers has become growing rapidly. For instance, in 2015 there were about 20.2 million; in 2016 there were about 31.3 million, and in 2017 there were more than 41.8 million. This shows a continuous increase in customers. Bulk-SMS is one of the value-added services provided by telecom companies, and it is used for broadcasting information to customers in the case of advertisement demands. Ethio Telecom has provided this service for the promotion of new services and products. In addition to this, it outsources the service to the third party.

Bulk-SMS advertisements are sent to customers almost always without prior knowledge of customers' interest. Due to this Ethio Telecom mobile subscribers receive a lot of SMS advertisements. These messages were either relevant or not to the recipients. Which means that the target customer was not identified. Due to this, customers are highly likely to find the messages disturbing and come up with a negative reflection on the service.

Companies have a plan and strategy for treating customers, i.e. understanding their customer groups and needs. This is really helping to build a positive image of the firms. Thus, it is important to assess the characteristics of bulk-SMS advertisements with respect to customers' responsiveness behavior and identify the level of satisfaction on the services. This will help the company to use optimal resource utilization by identifying the level of interest to service. In order to assess these kinds of problems, different researchers conducted on the approach of the analytical-descriptive method by preparing a questionnaire and develop a hypothesis. Since such studies are most likely subjective, it needs to study CDR data of bulk-SMS advertisements additionally.

1.3 MOTIVATION

Currently, it is most likely common to find users complain about SMS advertisements. Because too many messages received by telecom customers regardless of importance to individuals. It has not given attention to addressing "the right message to the right recipient concepts". Due to this, resource dissipation will not be controlled towards bulk-SMS advertisement. Customers are getting disturbed with irritating, unbearable generic and irrelevant text messages.

Therefore, customer identification based on their level of satisfaction will help to mitigate this problem. It will give a clue to improve the way of handling different bulk-SMS services with sustainable business continuity of the services using the analysis and interpretation of available customer data from Call Detail Record (CDR) and conducting field survey data.

1.4 RESEARCH QUESTIONS (RQ)

This research will answer the following research questions:

- RQ1: What are the main factors that affect customer attitudes towards customers' responsiveness of bulk-SMS advertising?
- RQ2: How far customers are willing to receive SMS advertising and who is a target customer for a specific promotion?
- RQ3: What are the level of customers' perception and responsiveness of bulk SMS advertisements?

1.5 RESEARCH HYPOTHESIS (RH)

- RH1: The perceived entertainment, informativeness, and credibility of mobile SMS advertisings do not have a significant positive influence on customers attitude towards responsiveness of mobile SMS advertising.

- RH2: The perceived irritation on bulk-SMS ads do not have a significant negative influence on customers attitude towards perception and responsiveness.
- RH3: The perceived privacy on bulk-SMS ads do not have a significant positive influence on customers attitude towards perception and responsiveness.
- RH4: The perceived relevance value on bulk-SMS ads do not have a significant positive influence on customers attitude towards responsiveness
- RH5: Customer attitude towards responding to bulk-SMS advertisement is not different between men and women.

1.6 OBJECTIVES

1.6.1 General Objective

The main objective of this research is assessing customers' perception and responsiveness behavior on bulk SMS advertising and identifying level of responsiveness.

1.6.2 Specific Objectives

The specific objective of this research includes:

- To identify key factors that influence customer attitude towards SMS advertisement.
- Customer classification based on responsiveness to SMS advertisements using data mining techniques.
- Formulating and validating hypothesis.

1.7 SCOPE OF THE RESEARCH

This study focused on assessing Ethio Telecoms' mobile customers specifically in Addis Ababa city. It mainly on bulk-SMS messaging relating to responsiveness attitude and identification of factors that affect customers' attitudes. Furthermore, customer classification includes based on their responses.

1.8 RESEARCH CONTRIBUTION

One of the most likely key assets in an organization is a customer. If customers are not interested in the services, they will not use it. Therefore, companies should give higher attention to them. This work gives a clue to conduct customer classification, based on an intensive assessment of customer attitudes on SMS advertising. In addition, this research will introduce the state-of-the-art practices of bulk SMS messaging and classify customers according to their level of responsiveness. After completion of this research, Ethio Telecom will be enriched with knowledge of customer behavior towards bulk-SMS advertisements, and this research will help as a foundation for further researchers in case of customer classification.

1.9 RELATED WORK

AIS (Advanced Info Service): the largest mobile phone service provider in Thailand) reports, 41 million SMS and 7.5 hundred thousand of Multimedia System (MMS) were sent in three days. Due to increasing the use of SMS and MMS as a marketing tool by several companies, the questions of effectiveness come up vitally growing. The roles of perception of these tools were studied effectively. There are factors considered to responsiveness attitudes i.e. demography, and relevancy of advertisement, brand familiarity, and attitude towards SMS & MMS [3].

As a finding, there are no significant factors from demography that affects attitudes. All factors have a direct relationship to attitude towards customer responses on SMS & MMS [3]. Marketers of many companies did not select target customers to send SMS and MMS, this will be exposed to resource dissipation & the paper recommended them to know information about target customers preference [3].

In [6] it was raised about investigating factors that affect customer attitudes i.e. intention, behavior, privacy, risk, incentive trust, and relevance. There were 232 among 250 consumers data were collected using simple random sampling methods. All hypotheses evaluated via test statistics parameters. All factors have a positive significant influence on mobile advertising acceptance. Finally, it concludes that all tested factors must be taken into implementation, i.e. permission-based campaign: means customers need to be able to remain in full control of their private information; push strategy: means awareness of mobile marketing service is very important in the early adoption stage etc.

The other related reviewed papers were studied about consumers' perception of SMS advertisements. It examines based on a cognitive, affective and conative attitude of subscribers and also considers location-based advertisements. One of them were used random sampling techniques the other one paper were used stratified sampling, and the validity of the sample tested with multiple linear regression. Informativeness does not affect customer attitude towards SMS advertisements in the first two papers [5],[6],[7].

Further it proves that the relationship between independent variables, such as entertaining, informative, credibility has significant positive effect on customer attitudes towards SMS ads. It has negatively affected by irritation factor and purchase behavior is negatively correlated with irritation. The other point is consent and location-based ads is more reasonable and acceptable than others [8],[9].

1.10 RESEARCH APPROACH (PROCESS)

A research approach is clearly shown in Figure 1.10.1 will help to meet the main objective of this study. In the first phase there are three activities are expected to be done, such as literature & document review and a CDR data collection. Secondly, the hypothesis will be formulated; Thirdly, it goes through designing research activity, i.e. providing questionnaires and conducting survey; In the fourth phase, survey data will be tested & analyzed; In the fifth phase, evaluate & analyze hypothesis. In addition to this, preprocessing of a CDR data will be executed here;

In six-phase customer classification will held using a field survey and a CDR data independently; Finally compare the two result.

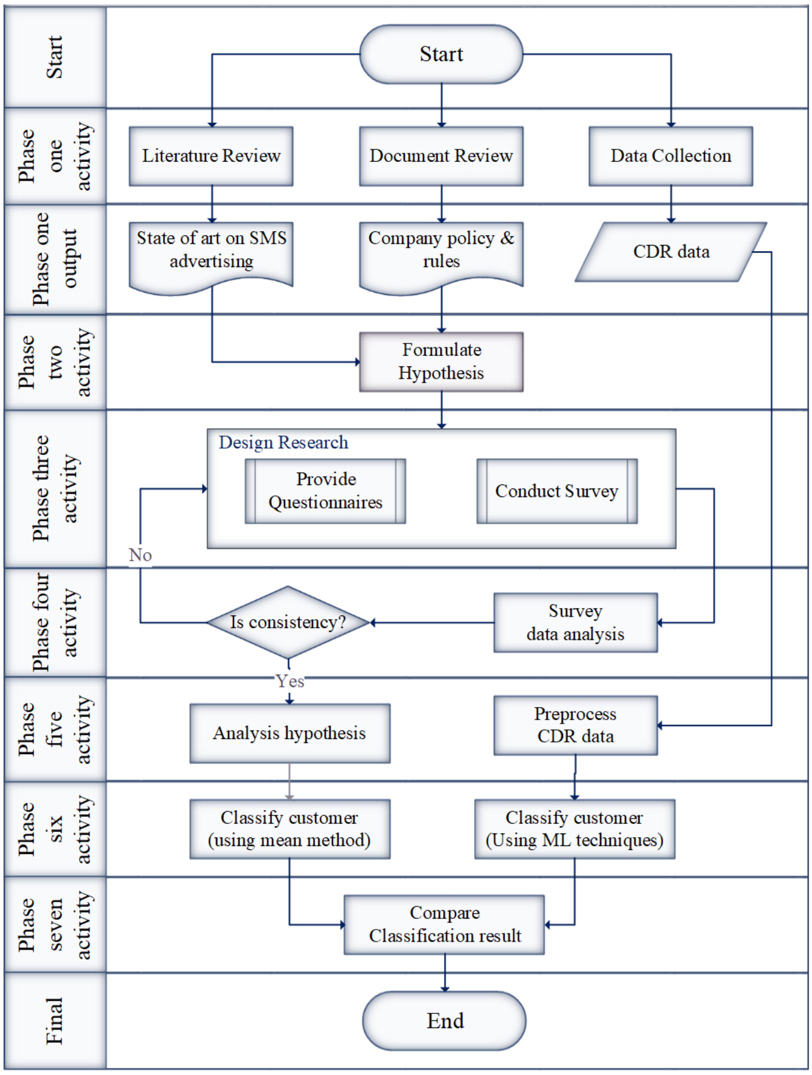

Figure 1.10.1: Research Process

1.11 RESEARCH REPORT ORGANIZATION

This thesis is organized as follows: Chapter 2 discusses the concept bulk-SMS ads, factors that affect customer attitudes. Chapter 3 about the concept of machine learning techniques. Chapter 4 contains a research design & methodology to make visible the work. Chapter 5 illustrates the discussion & results of two types of data sets with the statistical methods and selected machine learning techniques. Chapter 6 provides a conclusion, recommendation and future work.

2

BULK SMS ADVERTISEMENT

The chapter introduces the basic theory of bulk-SMS advertisement with respect to customer responsiveness behavior. An overview of scale factors that affect customer behavior towards responsiveness of SMS advertisement are also discussed. Conceptual framework of responsiveness to bulk-SMS advertisements has taken into consideration. Further it discussed about field survey analysis techniques.

2.1 MOBILE SMS ADVERTISEMENT

SMS advertising is one of the first mobile communications technologies to be applied in marketing. It is a new technological slogan for transmitting business-to-customer, and messages to mobile phones. SMS advertising is now a substantial source of revenue for many operators because it has been incorporated in the "instant messaging culture" among teenagers and young professionals [5].

Using the mobile channels, the response can be nearly immediate, interactive and the consumer can be reached everywhere at any time because the service is typically global. In fact, the mobile phone is the only advertising medium that consumers carry with them almost anywhere they go, so that mobile advertisements can be delivered to consumers without limitations regarding time and space [3].

According to [3], there were identified three consistent success indicators for SMS: (1) the cost-effectiveness and interoperability of the wireless infrastructure; (2) the high penetration of mobile phones (global penetration levels of some countries scored over 80%); and (3) the relatively low cost of the SMS messaging service.

Mobile advertising has typically been categorized into a push-model and pull-model. In the pull-model campaign, the marketer sends the information requested by the consumer; whereas in the push-model campaign, the marketer takes the initiative to send messages to the consumer [10]. The later model includes much of SMS advertising and raises the issue of consumers' permission. Since it is the marketer that initiates contact and communication, permission-based marketing refers to asking of consumers' consent to receive commercial messages while giving to individual an opportunity to stop receiving it at any time, and this approach can considerably reduce individuals' privacy concerns [10].

Short Message Service utilizes the use of standardized protocols to exchanging text messages between mobile devices and it usually carries a maximum of 160 characters and is sent wirelessly to another mobile device user. When a user sends a mobile SMS from his device, the message goes to the Short Message Service Centers (SMSC) to be stored and resend to a destination only when the destination mobile terminal/device is available on the network [10].

2.2 CUSTOMER PERCEPTION AND RESPONSIVENESS

According to [11] responsiveness refers to a consumer's willingness to respond and receive marketing communication. They argue that every marketing channel should be evaluated based on its responsiveness because this approach helps to understand the effects and effectiveness of communication. [11] stated that "an attitude is a person's enduring favorable or unfavorable evaluations, emotional feelings, and action tendencies toward some object or idea". Hence, a positive attitude toward mobile advertising refers to consumer favorable evaluations and willingness toward mobile advertising.

2.3 CUSTOMER ATTITUDE TOWARDS SMS ADVERTISEMENT

Attitude can be defined as a cultured inclination of human beings to show positive or negative mental thoughts more consistently towards any idea or object [2]. According to this context, attitude towards advertising is not limited to a specific thing, but it covers the whole exposure of advertising broad institution. In addition to this, different kinds of literature representations about attitude say as it is a favorable or unfavorable consistently ongoing response behavior of a person to a given entity or idea such as product, religion, TV program, advertising [10].

Structures of attitudes show how the consumer perceives the market stimuli (e.g. advertising) and how he reacts to them, and it combines three components or processes, i.e. cognitive, affective, and conative. Cognitive and affective components are unobservable mind order structures while conative is behavioral. Beliefs, thinking, understanding, evaluating, deciding are cognitive actions. Affective is expressed in feelings, moods, emotions and remembered sensations. Conation, on the other hand, refers to the intentions and actual behavior of the consumer [10].

2.4 FACTORS AFFECTING BULK SMS ADVERTISING

Factors that affect customer perception and responsiveness to bulk SMS advertisement should be studied in order to make an effective campaign and drag the customers' attention to the businesses are as follows:

2.4.1 *Entertainment*

Entertainment is the ability that satisfies consumers' desires for activity, deviation, and appealing enjoyment [12]. An entertaining dimension of advertisement is considered as one of the major factors that affect attitudes towards acceptance of advertisements. Customers usually develop a positive attitude towards an entertaining message [8]. According to [13] says entertainment seems to be a crucial factor for SMS advertising since it is the most significant factor that affects the respondent´s attitudes toward mobile advertising. Additionally, entertaining services can increase customer loyalty and add value to the customer.

2.4.2 *Informativeness*

Information dimension related to an advertisement is usually referred to as 'informativeness'. It is accepted as one of the noteworthy factors creating value for consumers & affects their attitudes towards ads [8]. Since the main focus of the advertisement is creating awareness for people and how the computing products or services are differing from each other, it is essential to provide information about new products and features among existing products and price changes [2]. A customer needs information quickly on the product that they are using or intended to use, and information can also be provided to them automatically [12].

2.4.3 *Irritation*

SMS advertising will be useful in providing timely information and results in a win-win situation for the customer as well as the SMS sender. Sometimes it may confuse as well as distract the potential customer. If advertisements are very frequent at unusual times of a day, it will irritate the customers. They may develop a negative opinion on the advertised product due to the feeling that the company wants to tie its inferior quality product to the customer by distracting them. When a consumer feels dishonor due to advertisements their attitude towards such advertisement will change, and they consider it as unsolicited message [12].

2.4.4 *Credibility*

The extent to which consumers believe in the claims and promises made by the brand is credibility. Credibility is consumers believe in the truthiness and the possibility of making claims happen in studied [12]. It is influenced by various factors, but most prominently influenced by corporation own credibility[2]. Perceived credibility distinct as, "The believability of consumers about the advertisement that offerings of a company will satisfy their needs and wants and also has a direct positive effect on respondents' attitude towards any ads or brand" [2].

2.4.5 *Relevancy*

As per [13] demonstrates the role of information and relevancy on the domain of SMS advertising, relevancy was noted as a key concept in understanding the advertisements. Because it is a primary component of all aspects of human communication. High relevancy can only be achieved by using reliable information related to the consumers' needs. Researchers have evaluate the relevant content of SMS advertisements from two viewpoints: first, sending SMS ads relevant to end-users' fields of interest will have a significant influence on perceiving it as valuable service. Second, SMS ads will provide more value for end-users if they are received at the appropriate times and locations. Other researchers found that customers were more likely to accept the messages with relevant content to them.

2.4.6 *Privacy and Permission*

Customers' privacy concerns include receiving unsolicited advertising messages, unauthorized personal data collection for marketing purposes, and deliberate theft of personal information. When permission & location-based advertisement provides a way to greater involvement and user control for customers, privacy concerns will tend to be reduced. These findings suggest a potential link between privacy concerns and advertising value[14].

2.4.7 *Demography*

Regarding to age, younger customers are more comfortable with looking at the ads. Although older consumers show a positive attitude towards mobile ads, they are comparatively more watchful whereas younger consumers show a much more satisfactory attitude towards mobile advertisement as compared to older once [12]. Gender plays a role in developing an overall attitude on cell phones. Men and women use and see mobile phones differently studied [12].

2.5 CONCEPTUAL MODELING FRAMEWORK

According to [10], cognition refers to the knowledge, beliefs or thoughts of the consumer about the advertisements; affective refers to the feeling and emotion that the consumer develops toward the product; conation refers to an intention to buy the product or the buying action itself. Attention, interest, desire, and action can, therefore, be rightly assumed outcomes of audience cognitive, affective and conative evaluation of some value promises of SMS advertisements. These values studied severally, as factors including entertainment, information, irritation, influence of appeal incentive, and general attitude towards SMS advertising.

The research framework is constructed based on literatures to illustrate the factors affecting customers' responsiveness attitudes toward bulk SMS advertising. Even though there are many factors investigated in different papers related to SMS ads, this study considers seven suitable factors with Ethiopian mobile customers' context. Therefore, this research attempts to study factors that affecting attitudes toward SMS advertising. The sign of (+ve or -ve) in the figure below shows, how factors either positively or negatively influences to attitude.

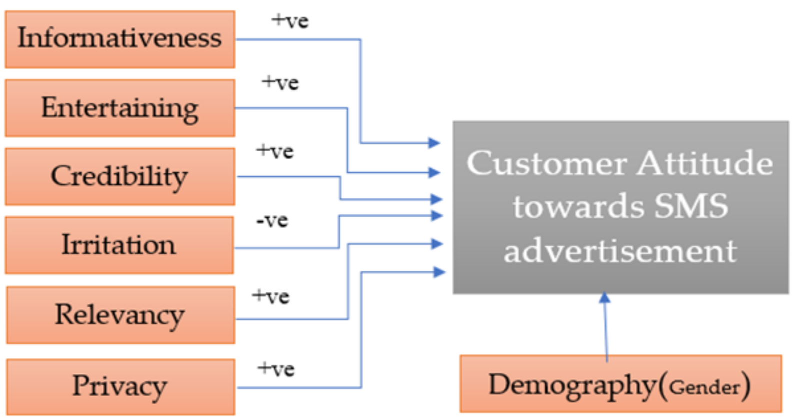

Figure 2.5.1: Conceptual framework for customer responsiveness factors.

2.6 FIELD SURVEY

According to [15], a survey is conducted to collect data from individuals to find out their behaviors, needs, and opinions towards a specific area of interest, traditionally with the intention to reach generalization. There are four commonly used modes of surveys for data collection. Such as face to face surveys, telephone surveys, Self-administered paper and pencil surveys, and Self-administered computer surveys(typically online). In this research, face-to-face surveying was applied.

A face-to-face survey is one of the most widely used methods of data collection. The response rate in this survey is always higher because the respondent trusts the researcher since it is in-person. The survey design in this research method is planned well in advance but there is scope to digress to collect in-depth data.

2.7 DATA ANALYSIS PROCEDURE TO FIELD SURVEY

Likert scale data analysis can be conducted into four levels of measurement, these levels are also referred to as a "Steven's Scale of Measurement" [15].

I. Nominal Scale

A Nominal scale can be based on natural or artificial categories with no numerical representation associated with it. Examples of nominal scale data include gender, name of a book, etc.

II. Ordinal Scale

It refers to an order or rank such as the ranking of students in a class, achievement, etc. With an ordinal scale, order or rank can be described, but the interval between the two ranks or order cannot be measured.

III. Interval Scale

An Interval scale shows the order of things and reflects an equal interval between points on the scale. It does not have an absolute zero. Measurement of temperature in degrees Fahrenheit or Centigrade is an example of an interval scale.

IV. Ratio Scale

A Ratio scale uses numbers to indicate the order and reflects an equal interval between points on the scale. It has an absolute zero. Examples of ratio measures include age and years of experience.

2.7.1 *Analyzing "Likert Scaled" Data*

Since, Likert scale data have ordered and equal intervals. Numbers assigned to a Likert scale have an ordered relationship to each other. It also reflects an equal interval between the points on the scale. Likert scale types described as 1= Strongly disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree. Due to these characteristics, Likert scale items fall into the interval measurement scale. Procedures to analyze interval scale items include arithmetic mean, standard deviation and Pearson's r correlation [15].

2.7.2 *Measure of Central Tendency using the Mean Method*

Central tendency is a single value that attempts to describe a set of data by identifying the central position within that set of data. The clusters formed by measuring central tendency are based on the domain and the requirements of the survey [15]. In this method, "mean" has been measured for each section of the survey in order to interpret respondents' answers to it.

2.7.3 *Reliability and Internal Consistency*

Reliability and internal consistency of research questionnaires were measured by "Coefficient of Cronbach's alpha test", discovered by Cronbach in 1952. Its' measurement value lays between 0.00 & 1.00. If the alpha value become 0.00 which means that there is no internal consistency. If it scores 1.00 it can be said that there is a perfect internal consistency. A Cronbach's coefficient alpha 0.7 means 70% of the variance in the score is reliable variance, whereas 30% of the score is an error variance. The other concept of this test is applying the composite score, which is treating items in groups, such as there may be two or more questions categorize in a single group [16]. Cronbach alpha were computed using Equation (2.1) [17].

$$\alpha = \left(\frac{k}{k-1}\right) * \left(1 - \frac{\sum_{i=1}^{k} \sigma_i^2}{\sigma_s^2}\right) \tag{2.1}$$

Where: σ_i^2 $\bar{\text{i}}$nter item variance; σ_s^2 = sample variance; k = number of items

2.7.4 *Statistical Tests*

In regard to test instruments, the following statistical test parameters were conducted to support the final result and analysis of this research. These are linear regression and z-test statistics.

A. Linear Regression

Linear regression involves finding the "best" line to fit two attributes (or variables) so that one attribute can be used to predict the other. For each unit value increases in one of the significant variables, there would be applied this line of regression formula [18]:

$$Y = \alpha + \beta X, \tag{2.2}$$

where Y = Dependent variable (Customer Attitude)

X = Independent variable; α = Constant(Intercept); β = Slope coefficient

But in case of this scenario better to use multiple linear regression, which is an extension of linear regression, because one dependent variable called attitude may related to many independent variables. Thus, it can be used that the following line of equation:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \beta_n X_n \tag{2.3}$$

B. Z- Test Statistics

Z-test is a statistical measurement based on the normal probability distribution and is used for judging the significance of several statistical measures, particularly the mean, median, mode, coefficient of correlation. It is worked out and compared with its probable value (to be read from the probability table) at a specified level of significance for judging the significance of the measure concerned. On the assumption that such a distribution tends to approximate normal as 'n' becomes larger. It is generally used for comparing the mean of a sample to some hypothesized mean for the population in case of a large sample [18].

3

MACHINE LEARNING

Machine learning is a data analytic technique that teaches a computer to do what comes naturally to humans and animals; it is the practice of applying algorithmic models to data, in an iterative manner. Due to this, a computer program discovers hidden patterns or trends that can be used to make predictions [19].

The subject of machine learning is one that matured considerably over the past several years. Machine learning has grown to be the facilitator of the field of "Data Science", which is, in turn, the facilitator of "Big Data". Machine learning, however, is not a totally new discipline; its general principles have been around for quite some time, just under different names: "data mining", "knowledge discovery in databases", and "business intelligence". These terms have been used to describe what is now called machine learning. Prior to that, "statistics" and "data analyses were terms used to describe the process of gleaning knowledge from data [19].

Machine learning algorithms use computational methods to "learn" information directly from data without relying on a predetermined equation as a model. The algorithms adaptively improve their performance as the number of samples available for learning increases [19]. Machine learning techniques can be classified in to three categories [20] and shown in Figure 3.0.1.

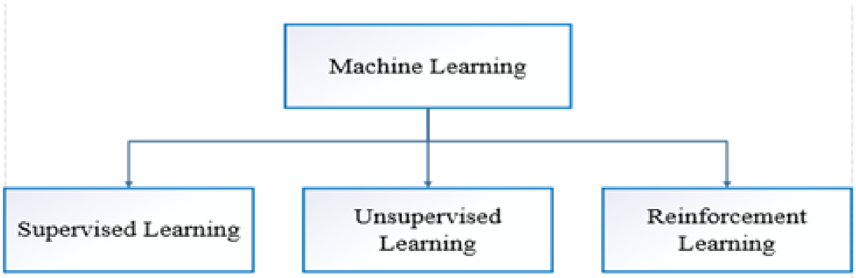

Figure 3.0.1: Types of machine leaning techniques [20]

3.1 SUPERVISED MACHINE LEARNING

Supervised learning is basically a synonym for classification [21]. The supervision in the learning comes from the labeled examples in the training data set. Input and output data are labeled for classification to provide a learning basis for future data processing. The term supervised learning comes from the idea that an algorithm is learning from a training dataset, which can be thought of as the teacher. Thus, supervised machine learning builds a model that makes predictions based on evidence in the presence of uncertainty [21].

3.2 UNSUPERVISED MACHINE LEARNING

Unsupervised learning is essentially a synonym for clustering. The learning process is unsupervised since the input examples are not class labeled. Typically, we may use clustering to discover classes within the data. For example, an unsupervised learning method can take, as input, a set of images of handwritten digits. Suppose that it finds 10 clusters of data. These clusters may correspond to the 10 distinct digits of 0 to 9, respectively. However, since the training data are not labeled, the learned model cannot tell us the semantic meaning of the clusters found [20]. Examples of this data mining techniques are clustering and association rule.

3.3 REINFORCEMENT/SEMI-SUPERVISED MACHINE LEARNING

Reinforcement learning is a class of machine learning techniques that make use of both labeled and unlabeled examples when learning a model. In one approach, labeled examples are used to learn class models and unlabeled examples are used to refine the boundaries between classes. For a two-class problem, we can think of the set of examples belonging to one class as the positive examples and those belonging to the other class as the negative examples [20], [21].

In reinforcement learning the network receives a logical or a real value after completion of a sequence, which defines whether the result is right or wrong. Intuitively it is clear that this procedure should be more effective than unsupervised learning since the network receives specific criteria for problem-solving [5].

3.4 supervised machine learning approaches(classification)

Classification is a form of data analysis that extracts models describing important data classes, such models, called classifiers, predict categorical class labels. Many classification methods have been proposed by researchers in machine learning, pattern recognition, and statistics. Algorithms are memory resident, typically assuming a small data size. Recent data mining research has built on such work, developing scalable classification and prediction techniques capable of handling large amounts of data set. Classification have numerous applications, including fraud detection, target marketing, performance prediction, and etc. [20],[21].

The general approaches to classification is a two-step process, consisting of a learning step (where a classification model is constructed) and a classification step (where the model is used to predict class labels for given data). In the first step, a classifier is built describing a predetermined set of data classes. This is the learning step, where a classification algorithm builds the classifier by "learning from" a training set made up of database tuples and their associated class labels.

A tuple, X, is represented by an n-dimensional attribute vector, X = (X1, X2, . . . , Xn), depicting n measurements made on the tuple from n database attributes, respectively, A1, A2, . . . , An. Each tuple, X, is assumed to belong to a predefined class as determined by another database attribute called the class label attribute. The class label attribute is discrete-valued and unordered. It is categorical (or nominal) in that each value serves as a class. The individual tuples making up the training set are referred to as training tuples and are randomly sampled from the database under analysis. In the context of classification, data tuples can be referred to as samples, examples, instances, data points, or objects [20],[21].

There were many supervised algorithms invented to solve the problem of classification and regression in real scenarios. This thesis considers only three algorithms. These are frequently used in literature, such as: Naïve Bayes, Multilayer Perceptron, and K-nearest neighbors algorithms.

3.4.1 *Naïve Bayes*

Naïve Bayes (NB) classifier is a probabilistic classifier which applies Bayes' theorem with strong independence assumptions [21],[22],[23],[24]. For each class value they estimate the probability that a given instance belongs to that class. It assumes that the effect of an attribute value on a given class is independent of the values of the other attributes. This assumption is called class conditional independence [24]. Bayes' rule determines that the outcome of an event can be predicted based on observations of some evidences [23],[25]. From Bayes' rule, we have:

$$P(H/E) = \frac{P(H) * P(E/H)}{P(E)} \tag{3.1}$$

Where: H and E are events

P(H) and P(E) are the prior probabilities of A and B without regard to each other

P(H|E), also called posterior probability, is the probability of observing event H given that E is true

P(E|H), also called likelihood, is the probability of observing event E given that H is true.

A Naive Bayesian model is easy to build, with no complicated iterative parameter estimation which makes it particularly useful for very large datasets. It is particularly suited when the dimensionality of the inputs is high [22],[23].

3.4.2 *K-Nearest Neighbors*

K-nearest neighbor (K-NN) is a non-parametric method used for classification and regression [22]. K-NN is a type of instance-learning, where the function is only approximated locally, and all computation is deferred until classification [22], [26].

The K-NN is among the simplest of all machine learning algorithms & in which the training data set is stored, so that a classification of a new data set may be found simply by comparing it to the most similar records in the training set [22], [26].

K-NN algorithm measures the distance between a query scenario and a set of scenarios in the data set. This distance can be computed using distance function d (x, y), where x, y, are scenarios composed of N features, such that $x = x_1, ..., x_n, y = y_1, ...y_n$. These are distance functions used in K-NN algorithms such as:

Euclidean, $D\,(x, y) = \sqrt{\sum_{n=1}^{k}\,(x_i - y_i)^2}$

Manhattan, $D\,(x, y) = \sum_{n=1}^{k} |x_i - y_i|^2$

Since the distance between two scenarios is dependent on the intervals, it is recommended that resulting distances be scaled such that arithmetic means across the dataset is 0 and the standard deviation 1 [22],[26]. Regarding strength, K-NN performs better with missing data, easy to implement and debug, provides more accurate results, noise reduction techniques are used to improve the accuracy [22]. Some of its weaknesses are its memory dependency, time-consuming, computational complexity and also its reliance on k-value.

3.4.3 *Multi-Layer Perceptron*

Multi-Layer Perceptron (MLP) is the most popular classification algorithm in Artificial Neural Network (ANN) [22],[27]. It is suitable for approximating a classification function and consists of a set of sensory elements that make up the input layer, one or more hidden layers of processing elements, and the output layer of the processing elements [20], [22]. The MLP with backpropagation (a supervised learning algorithm) is arguably the most commonly used and well-studied ANN architecture. It is capable of learning arbitrarily complex nonlinear functions to arbitrary accuracy levels, and its ability to process complex problems that a single hidden layer neural network cannot solve [27].

The successful application of neural networks to do the data analysis is MLP. These models are nonlinear neural network models that can be used for approximating a high degree of accurate prediction. [27].

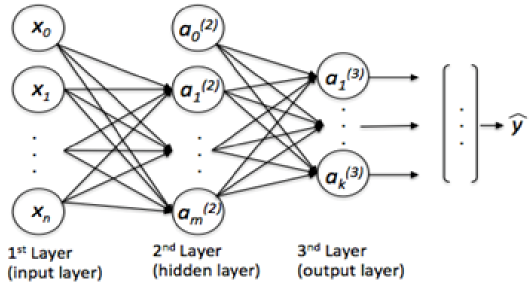

Figure 3.4.1: Basic architecture of multilayer perceptron (Neural Network) [27]

According to [28] the input layer receives the values of the independent variables as input, the nodes of the hidden layers take their inputs from the input layer process it and pass it to the node of output layer. A node receives information x from multiple nodes of the previous layer, these are multiplied by unique weight w and added together with a small value called bias as shown in Equation (3.2).

$$y = \sum_{i=1}^{n} w_i * x_i \quad + bias \tag{3.2}$$

3.4.4 *Data Cleaning*

Real-world data are often incomplete, noisy, uncertain, and unreliable. Information redundancy may exist among the multiple pieces of data that are interconnected in a large network [19],[29]. Since, it is a critical issue to be sure the validity of data for the success of data mining works, data cleaning has to be incorporated. Basic method of handling missing values in large data set as follows [19]:

Missing values:

- Ignore the tuple: This is usually done when the class label is missing (assuming the mining task involves classification). This method is not very effective, unless the tuple contains several attributes with missing values.

- Fill in the missing value manually: This approach is time consuming and may not be feasible given a large data set with many missing values.
- Use a measure of central tendency for the attribute (e.g., the mean or median) to fill in the missing value.
- Use the most probable value to fill in the missing value: This may be determined with regression, inference-based tools using a Bayesian formalism, or decision tree induction.

3.4.5 *Feature Selection*

Data contains many features, but all the features may not be relevant. So that feature selection is used to eliminate the irrelevant features from the data without much loss of the information. It is used to reduces the size of the problem, to improve the classifier performance by removing the irrelevant features and noise [20]. There are three types of feature selection: i.e. Filter, Wrapper, and Embedded feature selection methods [30].

Wrapper Method

The feature is dependent upon the classifier used. It uses the result of the classifier to determine the goodness of the given feature. It includes the interaction with the classifier and also takes the feature dependencies & drawback of this method is that it is slower than the filter method because it takes the dependencies also. The quality of the feature is directly measured by the performance of the classifier. Wrapper method is used to supervised learning algorithms [27].

3.4.6 *Data Aggregation*

Data aggregation is a process in which information gathered and expressed in a summary form. In simpler terms, it refers to combining two or more attributes into a single attribute, for statistical analysis of mean and variances. The purpose aggregation serves for data reduction, change of scale, and getting more stable data. The problem with aggregation is that it does not perform well with highly fluctuating data distributions [31].

A. Reduction

Reduce the number of objects or attributes. This results in smaller data sets and hence require less memory and processing time, and hence, aggregation may permit the use of more expensive data mining algorithms.

B. Change of Scale

Aggregation can act as a change of scope or scale by providing a high-level view of the data instead of a low-level view. Example, cities aggregated into regions, states, countries etc. Days aggregated into weeks, months & years.

3.4.7 *Performance Analysis Metrics*

A. Cross Validation

Cross-validation is a statistical method that evaluates and compares machine learning schemes by dividing data into train and test data sets. The train set is used to learn or train a model and the test set is used to validate the model. In practice, the training and validation sets must cross-over successively such that each data point has a chance of being validated against. K-Fold cross-validation is often used to minimize the bias associated with the random sampling of the training and hold-out data samples in comparing the baseline performance accuracy of two or more methods or classifiers [26]. Cross-validation can be used to estimate the test error rate using available training data[15].

B. Confusion Matrix (CM)

A confusion matrix is a useful tool for analyzing how well your classifier can recognize tuples of different classes. True Positive and True Negative tell us when the classifier is getting things right, while False Positive and False Negative tell us when the classifier is getting things wrong.

According to [22],[26] there is often a trade-off between the four performance measuring metrics in "real world" applications i.e. True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) measures.

Table 3.4.1: Confusion Matrix(3x3)

		Predicted Class			Predicted Class			Predicted Class		
		Positive	Negative	Negative	Positive	Negative	Negative	Positive	Negative	Negative
Actual Class	Positive	TP	FN	FN	TN	FP	TN	TN	TN	FP
	Negative	FP	TN	TN	FN	TP	FN	TN	TN	FP
	Negative	FP	TN	TN	TN	FP	TN	FN	FN	TP

C. Accuracy, Sensitivity and Specificity Measures

Accuracy: is the rate of the percentage of test set samples that are correctly classified by the model. The test set is independent of training set, otherwise over-fitting will occur [22],[23],[26].

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{3.3}$$

Classification error rate is known as 1 – Accuracy [19] ,[27], [32].

$$\text{Error\_rate} = \frac{FP + FN}{TP + TN + FP + FN} \tag{3.4}$$

Precision (P): is known as positive predictive value (the proportion of true positives of those that are predicted positives) [26]. It can be thought of as a measure of exactness (i.e., what percentage of tuples labeled as positive are actually such).

$$\text{Precision} = \frac{TP}{TP + FN} \tag{3.5}$$

Sensitivity: also known as recall or True Positive Rate (TPR) and measures the proportion of positives that are correctly identified [26]. It is a measure of completeness (what percentage of positive tuples are labeled as such). It will answer the question, how sensitive is the classifier to detecting positive instances.

$$\text{Sensitivity}(TPR) = \frac{TP}{TP + FP} \tag{3.6}$$

Specificity: is referred as True Negative Rate (TNR). measures the proportion of actual negatives that are correctly identified as such [19],[22][26].

$$\text{Specificity}(TNR) = \frac{TN}{TN + FP} \tag{3.7}$$

False Positive Rate (FPR) is the proportion of true negative that are incorrectly predicted as positive.

$$FPR = \frac{FP}{TN + FP} \tag{3.8}$$

False Negative Rate (FNR) is the proportion of true positives that are incorrectly predicted negative.

$$FNR = \frac{FN}{FN + TP} \tag{3.9}$$

D. ROC Curve

ROC curves are a useful visual tool for comparing classification models through evaluating the performance of classifiers [21]. ROC curve summarizes classifiers' performance over a range of trade-offs between TPR and FPR for a model. On the ROC curve, X-axis plotted to represents the percentage of false-positive; and Y-axis is to represent percentage (%) of true positive[22],[26]. .

E. F-Measure

F-measure is the weighted average of precision and recall. It takes both false positive and false negative into account. Intuitively it is not as easy to understand as accuracy, but F-measure is usually more useful than accuracy, especially if you have an uneven class distribution. Accuracy works best if false positive and false negative have similar cost. If the cost of false positive and false negative are very different, it is better to look at both precision and recall [26].

$$F - measure = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{3.10}$$

F. Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) is the square root of the mean of the squares of the values. It squares the errors before they are averaged and RMSE gives a relatively high weight to large errors. The most commonly used metric for determining the quality of fit is the RMSE. It measures the distance between the estimated response variable from the actual response variable [28].

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - y_i\ )^2} \tag{3.11}$$

4

RESEARCH DESIGN AND METHODOLOGY

This chapter has included a discussion of research methods and techniques applied in this study. These are data collection methods, data preprocessing approaches, classification techniques, and performance analysis metrics. Furthermore, it has included how rules developed and applied using the mean method into a CDR data set.

4.1 RESEARCH METHOD FOR FIELD SURVEY

In this study, the research followed a descriptive approach, which is a logical and appropriate approach to describe the current situation of bulk-SMS advertisement with respect to customers' responsiveness. Also, it considers different factors that affect the attitudes of customer perception and responsiveness on a bulk-SMS advertisement from Ethio Telecom customers' perspectives.

4.2 POPULATION

A one-month active mobile subscriber data extracted from Ethio Telecom network devices, specifically at Addis Ababa site. Starting from March 01, 2019, to April 02, 2019, and there were 4.49 million subscribers are using the services per each day. Thus, this study considers such a number as population size.

4.3 SAMPLING METHOD

A stratified sample is one that ensures the subgroups of a given population adequately represented within the whole sample population of a research study. There are many situations in which researchers would choose stratified random sampling over other types of sampling. First, it is used when the researcher wants to examine subgroups within a population. A stratified sample can also be smaller in size than simple random samples, which can save a lot of time, money, and effort for the researchers. Due to this type of sampling technique, the sample has high statistical precision compared to simple random sampling [32].

In-order to get fair sampling distribution, stratified sampling was used for this scenario. Which means dividing the total population of Addis Ababa mobile subscribers into six parts based on assigned location names by the company, such as North Addis Ababa Zone, South Addis Ababa Zone, West Addis Ababa Zone, East Addis Ababa Zone, Central Addis Ababa Zone, and South West Addis Ababa Zone. After identifying the office location of each zone, it was applied random sampling techniques. Then sample size determination was applied based on Taro Yamane, globally recognized sampling formula shown in Equation (4.1) and make it ready for statistical analysis.

$$n = \frac{N}{1 + Ne^2} \tag{4.1}$$

Where n - the sample size; N - the population size; e – acceptable sample error 95% Confidence level and p = 0.5 are assumed [3],[6],[9].

To determine the total number of sample sizes, this research has planned to conduct only Addis Ababa city mobile subscribers. This population size ware extracted from the system. Therefore, the number of customers who are using mobile services in Addis Ababa town shown in Section 4.2.

$$n = \frac{4490000}{1 + 4490000(0.5^2)} = 399.97$$

Even though, the minimum required sampling size for this population is 400 with a confidence level of 95% for such population size, this research considered 620 customers. Because increasing the sample size will decrease the sampling error.

4.4 DATA COLLECTION METHOD FOR FIELD SURVEY

In regards to data collection method, this research incorporates both qualitative and quantitative research methods. According to [18] the primary data means those which are collected afresh and for the first time, and thus happen to be original in character. The secondary data, on the other hand, are those which have already been collected by someone else and which have already been passed through the statistical process. Therefore, the primary data of this study were composed via questionnaires that contact in-person to individual.

In this study, 5-point Likert scale-based questionnaires were prepared with three languages i.e. Amharic, Afan Oromo, and English. All questionnaires coincide with scale variable that affects the customers' attitudes towards the responsiveness of bulk-SMS advertisements(ads), i.e. informativeness, entertaining, credibility, irritation,privacy, relevancy, and attitude.

To select a suitable method of analysis, the level of measurement must be understood first. For each type of measurement, there is/are an appropriate method/s that can be applied and not. Ordinal scales were used for this study to ranking or rating data that normally use integers in ascending or descending order.

In this stage, 50 mobile customers were conducted as a pilot survey to ensure the validity, consistency, and reliability of the questionnaires. A questionnaire contains two parts the first one has three demographic type quotations and the other one provided with 20 items which are about scale factors of SMS advertisement. After conducting different statistical tests and ensuring the validity and reliability of the questionnaires, it had been ready for large scale sample data collection.

In the large-scale data collection task, there had been 620 questionnaires distributed. Five hundred twenty of them were conducted in person directly. The other 100 were distributed using google form. In total 528 questionnaires returned. Which are 474 out of 520 and 54 out of 100 customers were reacted to the survey. Therefore, the study can successfully conduct 85% of the total distribution.

4.5 DATA PREPROCESSING FOR FIELD SURVEY DATA

Data preprocessing activity for a survey data includes data cleaning, data normality check, statistical validity, and data reliability & internal consistency.

4.5.1 *Data Cleaning*

Data cleaning tasks were held by segregating questionnaires that were filled incorrectly or with missed values. Then, all inadequate data has been deleted from the data set, to analyze and process usable, reliable, and valid information. Lastly, there were only four questionnaires were rejected due to improperly filled. Then data normality test was conducted to 528 cleaned responses.

4.5.2 *Data Normality*

The One-Sample Kolmogorov-Smirnov test procedure compares the observed cumulative distribution function for a variable with a specified theoretical distribution, which may be normal, uniform, exponential. It can be used to test that a variable of interest is normally distributed [18]. As per the results of the data normality test for this survey data of each variable, its' p-value is greater than 0.05 level of significance, thus the distributions for these variables are normally distributed.

4.5.3 *Statistical Validity of the Questionnaire*

It is a measurement of internal consistency using p-value and Pearson correlation to all variables. P-value is the probability of obtaining a result at least as extreme as the current one assuming null is true. In definition, it is the maximum acceptable probability of being wrong, if the alternative hypothesis is selected.

Table 4.5.1: Pearson correlation coefficient for internal validity test

Factors	**Statements & questions**	**Pearson Correlation**
Informative	I find SMS ads helpful and/or informative.	0.601
	I understand information in SMS ads easily.	0.614
	I receive SMS advertisements timely.	0.616
Entertain	I find most SMS ads enjoyable.	0.796
	I frequently use SMS with my friends.	0.796
	I like to receive and read SMS ads.	0.445
Credibility	I trust source of SMS ads from ethio telecom.	0.734
	I can easily identify the senders of SMS ads from ethio telecom.	0.734
Irritating	Receiving SMS ads makes me uncomfortable	0.521
	ET sends me too much redundant SMS ads frequently.	0.560
	I receive too frequent message for a single SMS ads.	0.503
	I find the content of SMS advertisement annoying.	0.559
Privacy	I trust private data collected by SMS advertisers will be respected.	0.605
	I don't like giving personal data in response to SMS ads	0.581
	I would like to be asked for my permission to receive SMS advertisements.	0.599
Relevancy	I think SMS advertisements are important.	0.688
	I personally find SMS advertisements relevant.	0.688
Responsive	SMS ads has led me to buy new service and /or product	0.481
	What is your action when you receive SMS ads?	0.438
	How frequently do you receive SMS advertisement on your mobile phone?	0.409

Unless there is an exceptional case based on engineering judgement, an acceptable p-value (alpha) is equal to 0.05. Thus, any p-value less than 0.05 means, reject the null hypothesis, otherwise fail to reject it. The other measuring point used in this study is Pearson correlation. It is a statistical method that determines the degree of relationship between two different variables known as bivariate statistics [18].

Internal validity test was conducted to pilot survey data in Section 4.3. The correlation coefficients between each question in one category and the whole field were measured, and Table 4.5.1 presents the results for each question. The p-values for all items are less than 5%, so the correlation coefficients of all items are significant at 5%. It can be said that all questions of each field are consistent and valid.

4.5.4 *Reliability and Internal Consistency*

Table 4.5.2 shows the test results of "Cronbach's Alpha" for each field of the questionnaire and the entire questionnaire. All items test results lays between 0.548 and 0.742, and this range considered as acceptable. It can be ensured that the reliability of each and all field of the questionnaire were secured. Cronbach's Alpha for the entire questionnaire is equals to 0.768 which is acceptable score.

Table 4.5.2: Internal consistency test for each questionnaires group

Factors	**No of questions**	**Cronbach's Alpha**
Entertaining	2	0.742
Informativeness	3	0.68
Credibility	2	0.634
Irritating	4	0.709
Privacy	3	0.66
Relevancy	2	0.548
Attitudes	4	0.578
Total items	**20**	**0.768**

4.6 CUSTOMER CLASSIFICATION TECHNIQUES USING SURVEY DATA

Customer classification was conducted using a statistical mean method on 528 customer responses. These responses are correctly completed as discussed in section 4.4. Steps to apply to mean method are demonstrated as follows [15]:

First: Identify the number of questions in each section. This number will be used to determine the mean for each section. It is recommended to calculate the mean for each section separately [15]. Adding them together may lead to an incorrect analysis. The number of questions in each section of the "SMS advertisement customer satisfaction survey" is shown in table 4.6.1.

Second: Add replied questions of each section (r) and divide it by the total number of questions in those factors. Thus, all responses to 'Informativeness' questions will be added and then divided by 3, as shown in table 4.6.1.

Third: Add the mean of all replied questions and divide it by the total number of sections in the survey. Since the total number of sections is 7, the mean of the seven sections will be added and then divided by 7. This result tells us each respondent's responsiveness attitude towards SMS advertisement.

Fourth: The results in step 3 can be interpreted according to the requirements. In the case of "SMS advertisement customer satisfaction survey", if the value is 3.5 or higher, it will be considered as "High Level of Responsiveness". If the value is 2.5 to 3.4, then it will be interpreted as "Medium Level of Responsiveness". If the value is 2.4 or lower, then it will be interpreted as "Low Level of Responsiveness".

Fifth: Repeat steps from first to forth for each survey tuple.

Table 4.6.1: Categories in “SMS advertisement customer satisfaction survey"

Ser. No.	Categories	Number of questions	Mean
1	Informativeness	3	$\frac{\sum_{i=1}^{3} r_i}{3}$
2	Entertaining	3	$\frac{\sum_{i=1}^{3} r_i}{3}$
3	Credibility	2	$\frac{\sum_{i=1}^{2} r_i}{2}$
4	Irritating	4	$\frac{\sum_{i=1}^{4} r_i}{4}$
5	Privacy	3	$\frac{\sum_{i=1}^{3} r_i}{3}$
6	Relevancy	2	$\frac{\sum_{i=1}^{2} r_i}{2}$
7	Responsiveness Attitude	3	$\frac{\sum_{i=1}^{3} r_i}{3}$

4.7 RESEARCH METHOD FOR CDR DATA

The other data set required for this research was CDR data. Since, data collection task primarily considers sampling, which is the main technique for data selection activities, this study randomly selects 10 short-code numbers that actually require a response from customers. Having these short-code numbers a one-month & half CDR extracted on a daily basis to the provided storage device by Ethio Telecom. A specific CDR data extracted for selected short-code numbers of bulk-SMS advertisement, using SQL-developer. It was 1,475,708 rows of CDR data extracted and ready for the preprocessing stage.

4.8 DATA PREPROCESSING FOR CDR DATA

Data to be used in any work should be identified, selected, and prepared for inclusion in the data mining model. This part involves the acquisition, integration, and formatting of the data according to the needs. The consolidated data should then be “cleaned” and properly transformed based on the requirements of the algorithm to be applied. New fields such as sums, averages, ratios, flags, and so on should be derived from the raw fields to enrich customer information, and to enhance the performance of the models [25].

In order to have these data from the system, Ethio Telecoms' Information System Division helps us by providing a daily CDR transaction from the system to a specific machine at large. Since this study considered only Addis Ababa mobile subscribers, data preparation coincides with respect to these specific data set.

A one and half month CDR data set were used from two data bases called Credit and Billing System (CBS) and VAS. A data that was collected from CBS data base contains 1,389,326 tuples with 33 attributes represents as received bulk-SMS by customers, and other 86,382 tuples with 141 attributes received by customers founds from Value Added Service (VAS) data base. There were also 168,325 messages responded among them during June to August 2019.

A CDR data size shown in the above paragraph were filtered using Addis Ababa mobile terminals' cell and site ID information with the help of SQL developer. According to the investigation possessed a CDR data of 419,249 bulk-SMS messages were dispatched for Addis Ababa city mobile subscribers. There were only 29,506 messages were got responses among the total of bulk-SMS advertisements.

Then all short-code numbers are replaced with new name with its' corresponding service types for the sake of data confidentiality. Such as for an entertaining type (Short Code Number (SC)_1: Says and modern life style advices, SC_5: Sport news & football player transfers, SC_7: questions & answers, SC_ 9: language Learn via text message, and SC_10: DSTV service); for informativeness type short codes (SC_2: vacancy, SC_3: life-style rules advice, SC_10 health Advice).

4.8.1 *Data Cleaning*

According to Section 3.4.4 data cleaning task included removing duplicate values, zero values, outliers, and wrong dates (or different from the selected boundary which is from June 28, 2019, to Aug. 18, 2019). Since duplicates and outliers are noisy for data analysis & evaluation, it has been expected to either removed or binned. As a result of this stage 233,174 row data were removed, and the remaining figures such as 186,075 and 29,249 are finally approved as net CDR data for received and responded bulk SMS ads respectively.

4.8.2 *Feature Selection*

Having feature selection concepts in Section 3.4.5, this research had conducted a wrapper method because the data used in this study requires classification based on the responses via supervised data mining techniques. A CDR data extracted from CBS and VAS database has 174 features. While looking at each attribute; nine of them are duplicates, sixty-six features have no values and the other ninety-three attributes were irrelevant to this subject. Due to these analyses, only six attributes are selected from a CDR data. Details of six attributed are shown in Table 4.8.1.

Table 4.8.1: Selected attributes from CBS and VAS data sets

No.	**Attributes from CBS**		**Attributes from VAS**	
	Feature Name	**Descriptions**	**Feature Name**	**Descriptions**
1	MSISDN	Mobile Number	ORGADDR	Originating number
2	CALLED NUMBER	Short code number	DESTADDR	Destination address (number)
3	CALL START TIME	Received/Sent Date and time	DELIVER TIME	Message sent date & time
4	CELL_ID	Location information	WRITETIME	Message received date & time
5			TIMESPAN	Time taken to respond
6			DESTIMSI	Location information

4.8.3 *Data Aggregation*

Based on data aggregation concepts stated in Section 3.4.6 a CDR data sets were counted, sum-up, averaged and scaled to make suitable data readiness for classification tool as follows:

SC_NUM (Shortcode number) There are many shortcode numbers were running via Ethio Telecom networks with different purposes but for this case, only ten shortcode numbers that need a response from customers were selected and renamed as SC_NUM1, SC_NUM2, . . . , SC_NUM10.

MO_NUM (Mobile number): In aggregated CDR data set there are 13,103 mobile numbers identified and these numbers renamed as MO_NUM1,. . . , MO_NUM13,103 for the sake of respecting the company's security policy.

RECI_CNT: It is counted the total number of bulk-SMS received within a given time period by individual customers.

RSP_CNT: The total number of responded bulk-SMS advertisements by individuals with a given time period.

TIME_SPAN: It is the length of time taken to make a response to received bulk-SMS ads numbers by individual customers.

ZONE_LOCATION: A place where customers frequently used the services. Finally, data aggregation result indicates that only 13,103 mobile cell phone customers were happy to be responding in different three levels, & ready for the experiment.

In order to identify the customer location area, all cell id had taken to evaluate the "mode" among frequent cell ids collected within a given time period. Thus, the largest mode was considered as it is the nearest home(living) area for individuals, or it tells how customers are using more time for telecom service in that specific area than the others. So that the selected cell id was mapped to a table that contains cell id, site id, and it's' corresponding specific location information for "Addis Ababa mobile stations. Therefore, location can be identified by zone.

4.8.4 *Data Transformation*

Data transformation is generalizing the data. Normalize all numerical attributes to (0,1). Data can be generalized to higher-level concepts. It is particularly useful for continuous-valued attributes. For example, numeric values for the attributed income may be generalized to discrete ranges i.e. low, medium, and high [29].

4.8.5 *Derived Attributes*

An extended list of relevant fields was prepared for the needs of the analysis, to provide a complete view of each customer regarding different characteristics. This list included derived attributes such as monthly averages and ratios (percentages of total balance and of total transactions) which denoted the dominant product categories and the most common types of transactions for each customer [21].

Therefore, derived attributes for this study are service usage (percentage of responses over received bulk SMS advertisements); time elapsed to respond a message; time flag used to categorize instances according to the time span. The time span was computed by taking the average of all individuals time elapsed to response and then normalized to 0 & 1. For instance, if a customer scores less than 0.3 to responds a message, it can be considered as "Short time to respond SMS ads (STS)", and if a customer's scores between 0.3 and 0.5, can be considered as "Average time to respond SMS ads (ATS)", otherwise categorized as Long time to respond SMS ads (LTS)", the other last attribute is a class attributes called "Level of Responsiveness". It is derived based on all aggregated & derived attributes.

4.9 CUSTOMER CLASSIFICATION TECHNIQUE USING CDR DATA

Customer experience can be classified into three i.e. High level, Medium level, and Low-level satisfaction, using statistical method [33]. In order to make suitable for this study, rules have been developed based on the number of responses and time elapsed to respond that SMS advertisement.

While extracting rules, the mean method discussed in Section 4.6 was used for the categorization of customers. Such that scale value of 3.5 was converted to a percentage of 70%((3.5/5)*100), and taken into account as a highly responsive customer(HR), the second level score converted as 50% ((2.5/5)*100). If any score lies between 50% and 70%, it will consider as medium level responsive customers(MR), and the rest of them are low-level responsive customers(LR). Since there are three levels for customer satisfaction expected to be produced, this thesis, had tried to make a combination between the number of responses & time taken to the response. The number of responses and time elapsed to respond were categorized into three levels.

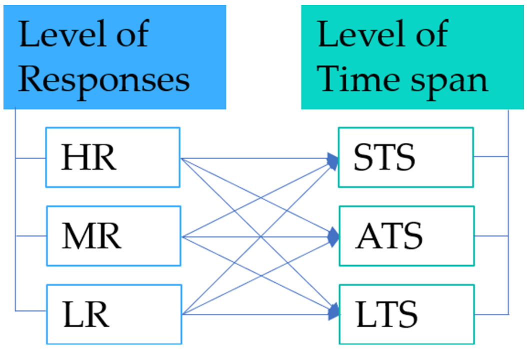

Figure 4.9.1: Possible combination of two sets/categories

The relation between the level of responses and time taken to respond shown in Figure 4.9.1 which are a possible combination of the two categories.

Aggregated CDR data were labeled for each instance based on the measurement results of selected attributes such as a number of responses over received SMS, and time elapsed to make a response on average for each customer to those selected shortcode numbers discussed in Section 4.7. Data labeling tasks consider rules extracted based on the possible combination of two attributes results. There are exactly nine rules that were developed on the aggregated data set. After pruning similar rules the study has reached exactly six merged rules for categorization.

Table 4.9.1: Finally pruned rules

No.	**If (Response/Received SMS ads) is...**	**... if (time elapsed to respond) is...**	**...then labeled as:**
1	Greater than 0.7	Less than or equal to 0.5	HLR customer
2	Equals to (0.5 - 0.7)	less than 0.3	HLR customer
3	Greater than 0.7	Greater than 0.5	MLR customer
4	Equals to (0.5 - 0.7)	Equals to (0.3 - 0.5)	MLR customer
5	Less than 0.5	Less than 0.3	LLR customer
6	Less than or equals to 0.7	Greater than or equals to 0.3	LLR customer

After labeling all tuples of CDR data, classification was conducted via machine learning tools, called Weka 3.9.3. Three algorithms were applied using 10-fold cross-validation and percentage split test options, i.e. naïve Bayes, k-nearest neighbor, and multilayer perceptron.

5 RESULTS AND ANALYSIS

This chapter discusses two different types of experiment results and analyses from a different data set. These are questionnaires and a CDR data specifically for bulk-SMS advertisement responses. Upon the experiment test results and analysis of the study, all research questions had been addressed. In addition to these, it conducts a supervised machine learning scheme to classify a CDR data. This will reinforce an independent or subjective outcome from the survey analysis. The statistical mean method was applied for the field survey data and classification techniques applied to a one-month CDR data for a specific short-code number that necessarily requires a response to every SMS text.

5.1 DATA ANALYSIS FOR SURVEY DATA

As per Section 4.4 there had been used 528 suitable customers for a survey data analysis. Because those respondents were filled out the entire questionnaire correctly. These survey data were grouped based on gender, age, and location.

According to the analysis result, using SPSS v21 package, the descriptive status of gender and age are shown in Table 5.1.1. Upon a large scale sample population study, 56% of the respondents are female and the other 44% are male customers. In regard to age categories 48% of the survey largely covered by people who are between 18 and 25 years old, and the next large number of a mobile subscriber (47%) can be found between the age of 26 to 35 years old. This implies that most of Ethio Telecoms' mobile subscribers are between 18 & 35 years old.

In regards to sampling collections. It was conducted based on locations, 98 (19%) of responses were from CAAZ, 93 (18%) of were from NAAZ, 87 (16%) of the responses were from SWAAZ, and SAAZ & EAAZ were contributed 17% each to this survey.

Table 5.1.1: Distribution of respondents by demography

Gender:	Age Categories(in years)				Total	
	18 - 25	26 - 35	36 - 45	46 - 55	Frequency	Percentage
Male	96	111	24	2	233	44%
Female	157	135	3	0	295	56%
Total	253	246	27	2	528	100%

5.1.1 *Analysis of Items in Each Categories*

A statistical test was conducted for each item in a group as per its' categories based on scale factors. Upon the test results the mean, test-value, and p-value had been taken for the analysis and discussion. Details are shown in Table 5.1.2.

Table 5.1.2: Details of test results for all scale factors

Informativeness						
No.	Items	Mean	SD	Proportional mean	Test value	P-Value
1	I find SMS ads helpful and/or informative.	2.86	1.08	57%	-3.08	0.00
2	I understand information in SMS ads easily.	2.46	1.08	49%	-11.44	0.00
3	I receive SMS ads timely.	2.60	1.13	52%	-8.23	0.00
Entertaining						
1	I find most SMS ads enjoyable.	2.86	1.08	57%	-0.17	0.00
2	I frequently use SMS with my friends.	2.46	1.08	49%	0.06	0.04

Credibility						
1	I trust source of SMS ads from ethio telecom.	2.41	1.13	48%	-12.03	0.00
2	I can easily identify the senders of SMS ads from ethio telecom.	3.49	1.21	70%	9.39	0.00
Irritation						
1	Receiving SMS advertisements makes me uncomfortable.	3.40	1.20	68%	7.65	0.00
2	Ethio telecom sends me too much redundant SMS ads frequently.	4.14	0.90	83%	29.02	0.00
3	I receive too frequent messages for a single SMS advertisement.	3.73	1.02	75%	16.49	0.00
4	I find the content of SMS ads annoying.	2.72	1.13	54%	-5.64	0.00
Privacy						
1	I trust private data collected by SMS ads will not be respected.	3.14	1.06	63%	3.05	0.00
2	I don't like giving personal data in response to SMS ads.	3.44	1.10	69%	9.24	0.00
3	I would like to be asked for my permission to receive SMS ads.	2.79	1.17	56%	-4.18	0.00
Relevancy						
1	I think SMS ads are important.	3.77	1.03	75%	17.27	0.00
2	I personally find SMS ads relevant.	2.85	1.27	57%	-2.66	0.01
Attitude towards bulk SMS ads						
1	I like to receive and read SMS advertisement.	3.02	1.06	60%	0.45	0.65

2	SMS ads has led me to buy new service(s) and /or product(s).	3.02	1.30	60%	0.43	0.66
3	What is your action when you receive SMS advertisement?	3.05	0.99	61%	1.05	0.29
4	How frequently do you receive SMS ads on your mobile phone?	3.20	1.18	64%	3.92	0.00

5.1.1.1 *Analysis for "Informativeness"*

According to the test results shown in Table 5.1.2, the mean, test value, and p-value of the scale factor "Informativeness" are equal to 2.75 (55%), –6.261, and .000 respectively. Since the p-value is less than the level of significance ($\alpha = 0.05$) and the sign of test result is negative, the mean of this field is significantly less than the hypothesized value 3. There were 55% of the respondents disagree with all items of informativeness. Thus, it can be concluded that most of the respondents were received the bulk SMS advertisements which were not helpful, not easily understandable, and not timely.

5.1.1.2 *Analysis for "Entertaining"*

According to test results revealed in Table 5.1.2, the mean, test value, and p-value of scale factor "Entertaining" is equal to 2.71 (54.2%), -8.563 and .000 respectively. Since the p-value is less than the level of significance ($\alpha = 0.05$) and the sign of test result is negative, the mean of this field is significantly less than the hypothesized value 3. Thus, it can be said that respondents disagree on the scale factor "Entertaining". Briefly, speaking all respondents do have a concrete answer to this service in details and it implies that bulk-SMS advertisements are not entertaining or enjoyable.

5.1.1.3 *Analysis for "Credibility"*

Based on the results disclosed in Table 5.1.2, about credibility factor, its' mean, test value and p-value are 2.940 (58.8%), -1.584 and .014 respectively. Since the p-value is less than the level of significance ($\alpha = 0.05$) and it' negative test results, the mean of this factor is significantly smaller than the hypothesized value 3. Thus, 52% of the respondents were disagreed by a sense of credibility to bulk-SMS advertisements. Customers feel that SMS ads are not trustful.

5.1.1.4 *Analysis for "Irritation"*

An irritation scale factors was tested with the same statistical tools and as the result discussed in Table 5.1.2, the mean of "Irritating" equals 3.03 (61%), Test-value = 0.783, and p-value = .434. P-value is greater than the level of significance ($\alpha = 0.05$). The sign of the test value is positive, so the mean of this field is insignificantly greater than the hypothesized value 3. This result implies that the respondents agreed to the statements of "Irritating". In fact, 61% of the customers are receiving too frequent messages for similar content and its' redundancy makes people uncomfortable and annoying. Therefore, the nature of SMS advertising works against its acceptance from customers.

5.1.1.5 *Analysis for "Privacy"*

As per the test result shown in Table 5.1.2 mean of scale factor "Privacy" is equals 3.1 (62%), Test-value = 3.44 and P-value = 0.001 P-value is less than the level of significance ($\alpha = 0.05$). The sign of the test result is positive. Therefore, the mean of this field is significantly greater than the hypothesized value 3. The result tells that 62% of the respondents agree to all items stated in the field of "privacy". It can be concluded that customers do not have trust in giving personal data via SMS ads and hardly needs to be asked permission before receiving any message.

5.1.1.6 *Analysis for "Relevancy"*

The mean, test value and p-value of the scale factor "Relevancy" are 3.3 (66%), 8.38 and 0.000 respectively. The p-value is less than the level of significance($\alpha = 0.05$), and with positive test value. Therefore, the mean of this field is significantly greater than the hypothesized value 3. Thus, it can be conclude that respondents were disagree by the relevancy of bulk-SMS advertisement. To sum up this test, customers feel & react that SMS ads is not important. Details shown in Table 5.1.2.

5.1.1.7 *Analysis for "Responsiveness Attitude towards Bulk-SMS Advertisements"*

The mean of the field "Attitudes towards SMS advertising" shown in Table 5.1.2 is equals to 2.96 (59.2%), Test-value = -1.121, and P-value = 0.263. P-value is greater than the level of significance (0.05). Since, the sign of the test value is negative, the mean of customers' attitude towards responsiveness is insignificantly smaller than the hypothesized value 3. Accordingly, it can be concluded that the respondents disagree with this field "Attitudes towards SMS advertising". Customers do not be enforced to buy new services due to the influence of bulk-SMS ads.

5.1.2 *Summary for all Scale Factors Analysis*

Table 5.1.3 shows the summary of field survey test result for SMS advertisement factors on customer attitude. Since, the p-value of scale factor "Relevancy" and "Privacy" is less than the level of significance (p-value = .000 < α= 0.05), the mean of these scale factors are significantly grater than the hypothesized value 3. Based on the responses, the respondents become neutral and/or disagree by the relevancy of bulk-SMS advertisement and agree to field of "privacy". This means that customers do not have trust in giving personal data via SMS advertisements and they seriously needs to be asked permission before receiving any message.

The other three scale factor i.e. "Informativeness", "Entertaining", and "Credibility" have significantly smaller mean values than the hypothesized value. Because these factors had scored a smaller p-value than level of significant. Furthermore, 55% and higher of the respondents were disagree to all items stated in this three scale factors. Which tells that bulk-SMS advertisements are not helpful, not easily understandable, not timely, not entertaining, and customers feel that not trustful.

Table 5.1.3: Mean and test value for "SMS advertisement factors on attitude"

No.	Factors	Mean	SD	Proportional mean(%)	Test value	P-Value
1	Informative	2.75	0.91	55	-6.261	0.000
2	Entertaining	2.71	0.79	54.2	-8.563	0.000
3	Credibility	2.94	0.87	58.8	-1.584	0.014
4	Irritating	3.03	0.76	61	0.783	0.434
5	Privacy	3.1	0.738	62	3.44	0.001
6	Relevance	3.3	0.87	66	8.38	0.000

The mean is significantly different from 3.

An "Irritation" factors are significant to influence customer attitude towards the responsiveness of bulk-SMS advertisement. Because, the mean, test value, and p-value of irritating factors equal to 3.03 (61%), 0.783 and 0.434 respectively. Its' p-value is greater than the level of significance (α = 0.05), and its' positive test value indicates the mean is significantly greater than hypothesized value 3. Therefore, this result implies, receiving too frequent messages for similar content and its' redundancy makes people uncomfortable and annoying. Due to its' higher score of mean, irritating can consider being the main factors that influence customers' attitudes towards responsiveness on SMS advertisement.

Generally, customers do not think that SMS advertisements offer important information and entertaining, besides it is more irritating and less credible. However, they think the most important factor is irritating. because receiving too frequent messages for similar content and its' redundancy makes people uncomfortable and annoying.

5.1.3 *Analysis of Scale Factors using Multiple Linear Regression*

According to multiple linear regression analysis results shown in Table 5.1.4, some of the independent variables have less impact on consumer's attitudes towards SMS advertising. The R^2 value is 0.821. Its' value shows that there exist 82.1% influences on variation customers' attitude towards the bulk-SMS advertisement is explained by scale factors of "Entertaining, Credibility, Irritation, and Privacy". Furthermore, the analysis of variance for the regression model is F = 341.646, significance(sig.)= 0.000. This implies that there is a significant relationship between dependent variable customer attitude and independent variables".

Table 5.1.4: Multiple linear regression

Variables	β	**Z - test**	**P-value**	R^2	**F**	**Sig.**
(Constant)	0.730	8.351	0			
Informativeness	-0.004	-0.175	0.861			
Entertaining	-0.067	-3.151	0.002			
Credibility	0.083	4.210	0.000	0.821	341.646	0.000*
Irritating	0.928	2.488	0.000			
Privacy-based	-0.018	2.538	0.025			
Relevancy	-0.32	-1.324	0.186			
Dependent Variable is 'Attitude'						

It is practical to check the validity of the hypothesis using linear regression. As a result, shown in Table 5.1.4, the independent variable "Informativeness" and "Relevancy" has no influence on responsiveness attitude towards bulk-SMS ads in this context. Because, the test result for p-value is 0.861 and 0.186 respectively, which is greater than the significance level 0.05. So, it can be said that there is no significant influence on attitude due to lack of "Informativeness" & "Relevancy", which means SMS advertisement is not informative and less relevant in this scenario.

In the line of the regression equation for each one-unit changes for instance, in the informativeness of SMS advertisements, customers' attitudes will change by -0.067.

Y = 0.730 + (-0.067X). Therefore, the estimated multiple regression equation for customer attitude towards responsiveness is:
Consumer attitude (CA) = 0.730 + 0.928 (Irritation) + 0.083 (Credibility) + (-0.018) (Privacy) + (-0.067) (Entertaining) + 0.004 (Informativeness) + (-0.032) (Relevancy). Consequently, these results validate factors that exists a significant positive effect on a bulk-SMS advertisement, like entertaining, informativeness, credibility, privacy and relevancy and the other factors which is irritating contribute a significant negative influence on bulk-SMS ads in this study.

5.1.4 *Research Hypothesis (RH) Test Result Interpretation*

This research conducts a z-test with two-tailed 5% level of significance, and it's corresponding z-critical boundary value of -1.96 and 1.96 based on [18]. Any test results scored beyond this boundary were rejected. All hypotheses concerned the relationship between customers' responsiveness attitude and factors like informativeness, entertaining, credibility, irritating, privacy, relevancy and demographic.

Research hypothesis one divided into three sub-parts such as tests concerning informativeness, entertaining, and credibility.

5.1.4.1 *Hypothesis One Test Result Analysis for "Informativeness"*

The test result of informativeness factor shown in Table 5.1.4 was ($z = -0.175 <$ at $p < 0.05$), and it discloses how this factor was not significantly affects responsiveness attitude towards bulk-SMS advertisements. Because, its' p-value 0.861 is greater than the required significance level, and its z-test statistics value -0.175 which was found in the boundary region of z-critical ($Z = \pm 1.96$). Therefore, this result implies that failed to reject the null hypothesis. In addition to this, the correlation coefficient, R test shown in Table A.1.1, indicates a positive relationship between informativeness and customer attitude towards the responsiveness of SMS advertisements (0.247).

The respondents' reflection did coincides with the null hypothesis, and it can be said that customers are like to receive an SMS advertisement with an informative plus. So, they will be influenced with informative type of SMS advertisements.

5.1.4.2 *Hypothesis One Test Result & Analysis for "Entertaining"*

This hypothesis was tested for its impact validation of entertaining factors on customers' perception and responsiveness attitude towards bulk-SMS advertisements using p-value and z-test statistics. The test result ($z = -3.151 <$ at $p < 0.05$) shown in Table 5.1.4 indicates that the entertaining factor does have an insignificant influence on responsiveness attitude towards bulk-SMS ads in the case of Ethio Telecoms' customers. Because an entertaining variable has a p-value of 0.002 which is less than the required significance value and also its' z-test statistics value(-3.151) is less than z-critical (-1.96) at $p<0.05$, then the null hypothesis was rejected.

In addition to this, the correlation coefficient, R test shown in Table A.1.1 indicates that there is a positive relationship between entertaining and customer attitude(0.238). Therefore, the respondent reflection did not coincides with the null hypothesis, & it can be said that customers can be influenced by an entertaining factors to respond to bulk-SMS advertisement.

5.1.4.3 *Hypothesis One Test Result & Analysis for "Credibility"*

Credibility test result shown in Table 5.1.4 is ($z = 4.210 >$ at $p< 0.05$), which means there exists a statistically significant influence on responsiveness attitude by credibility. Because, it has a p-value of 0.000, which is less than the required level of significant, and its z-statistics value lays beyond the boundary of z-critical at $p<0.05$. It implies that reject the null hypothesis and accept an alternative one.

Therefore, the respondents' interest did not coincide with the expected hypothesis, and it can be said that customers are like to receive SMS ads with more credibility.

5.1.4.4 *Research Hypothesis Two Test Result Analysis for "Irritation"*

Test result for irritating variable in Table 5.1.4shows ($z = 2.488 >$ at $p< 0.05$) which means, the perceived bulk-SMS advertisements were irritating and exists statistically significant influence on responsiveness attitude. Because, its' p-value 0.000 is less than the required significance level of 0.05, and its' z-statistics value ($z = 2.488$) did not lay between the boundary value of z-critical. Therefore, this result implies to reject the null hypothesis and accept an alternative one.

Most of the respondents' reflection was coincide with the expectation, and it can be said that customers do not want to receive the redundant, irritating and annoying contented types of bulk-SMS advertisements.

5.1.4.5 *Research Hypothesis Three Test Result Analysis for "Privacy"*

The third hypothesis has a p-value of 0.025 which is greater than the required significance level at 0.05, and the corresponding z-statistics score is 2.538, which is beyond the boundary of z-critical points at 5% significance level. Thus, it can be said that there was a statistically significant positive influence on responsiveness attitude by privacy. Since, the result of this experiment is significant, better to reject the null hypothesis and accept an alternative one. Furthermore, the correlation coefficient R test shown in Table A.1.1 indicates that there is a positive relationship between privacy and customer attitude towards SMS advertisements.

Customers did not agree with this hypothesis, and it can be said that they do have a strong concern about privacy issues while receiving SMS advertisement. That means they need to be asked permission before receiving any SMS advertisement. Therefore, the privacy of personal information has to be guaranteed.

5.1.4.6 *Research Hypothesis Four Test Result Analysis for "Relevancy"*

Test result for relevance variable shows ($z = -1.324 <$ at $p< 0.05$) which means, there exists a statistically insignificant influence on responsiveness attitude by relevance type of SMS advertisement. Because, it has a p-value of 0.186, which is greater than the required significance level 0.05, and its z-test statistics value (z = -1.324) lays between the boundary value of z-critical at p<0.05, therefore this result implies to accept the null hypothesis. Moreover, its' correlation coefficient R test shown in Table A.1.1 indicates a negative relationship between relevancy and customer attitude towards responsiveness to the bulk-SMS advertisements (-0.207).

5.1.4.7 *Research Hypothesis Five Test Result Analysis for "Demographic"*

According to the demographics test result analysis, the p-value for all factors except irritation was scored higher than the level of significance($\alpha = 0.05$). Hence, there is an insignificant difference among respondents on these majority factors due to gender. So, it can be concluded that the personal behavior of respondents' by gender has no effect on responsiveness due to these factors. Unfortunately, the irritating factor has a p-value smaller than the level of significance 0.05, which means there existed a significant difference among the respondents towards irritating due to gender. So, it can be concluded that the personal behavior of respondents due to gender has only an effect on irritating factors.

The mean of male respondents are higher than female respondents, which implies that males are near to try things directly and plain information about the services is enough to them but females are wise to things, they like to visualize the services before buying. To sum up this analysis gender didn't influence to responsiveness attitudes due to the majority of factors are insignificant. So, it can be accepted.

5.1.5 *Summary of RH Analysis Results*

To summarize the analysis of survey data, all factors such as Informativeness, Entertaining, Credibility, Privacy, and Relevancy were positively correlated with responsiveness attitude towards SMS advertisement based on demography. Informativeness and credibility were correlated more to consumers' positive attitudes towards bulk-SMS, than the other factors. Since one of the research questions is identifying factors that affect customers' responsiveness attitude towards SMS ads, this study examined all scale factors using field survey data. As discussed in Section 2.7.4, there are statistical values that help to evaluate customer responses like z-test statistics that applied to all scale factors and compared with critical values (z-critical = ±1.96) from probability distribution table at 5% level of significance.

Beforehand, the study considers the null hypothesis as it does not have a positive significant influence to change the customer responsiveness attitude. Upon test results shown in Table 5.1.4 Informativeness and Relevancy do not have a significant impact on attitude at a p-value of 0.05 level of significance and its' z-test statistics values were also scored not beyond the boundary of critical region. Therefore, these factors do not have a significant influence on customer attitude towards responsiveness, and the interpretation of the findings tells us, the null hypothesis was accepted. This means scale factors Informativeness and Relevancy do not have an impact on the responsiveness attitude of customers to SMS advertisements.

The other test result for scale factors such as; Entertaining, Credibility, Irritating, and Privacy has a p-value less than level of significance at ($\alpha = 5\%$), and their z-test statistics were scored beyond the boundary of critical region (z-critical = ± 1.96). Thus, this finding interpretation shows all null hypotheses were rejected. Because these factors do have a measured impact on customer attitude in regard to responsiveness to SMS advertisement. Finally, the summary of hypotheses results shown in table 5.1.5.

Table 5.1.5: Summary of Hypothesis Test Result

Null Hypothesis	Z-Score	P-Value	Decision
'Informativeness' do not have impact on 'Attitude'	-0.175	0.861	Accept
'Entertaining' do not have impact on 'Attitude'	-3.151	0.002	Reject
'Credibility' do not have impact on 'Attitude'	4.210	0.000	Reject
'Irritating' do not have impact on 'Attitude'	2.488	0.000	Reject
'Privacy' do not have impact on 'Attitude'	2.538	0.025	Reject
'Relevancy' do not have impact on 'Attitude'	-1.324	0.186	Accept

5.2 RESULT OF CUSTOMER CLASSIFICATION USING FIELD SURVEY DATA

According to the mean method data analysis discussed in section 4.6, customer can be classified into three categories based on their level of responsiveness such as 83 (16%) of the customers are categorized to "High-level satisfied customer", the other 234 (44%) of customers can be categorized to medium level satisfied customers with this service. Finally, the last portion of customers which is 211 (40%) of them were categorized as "Low-level satisfied customers". These customers are highly affected by this service and they do not have positive implies to the service.

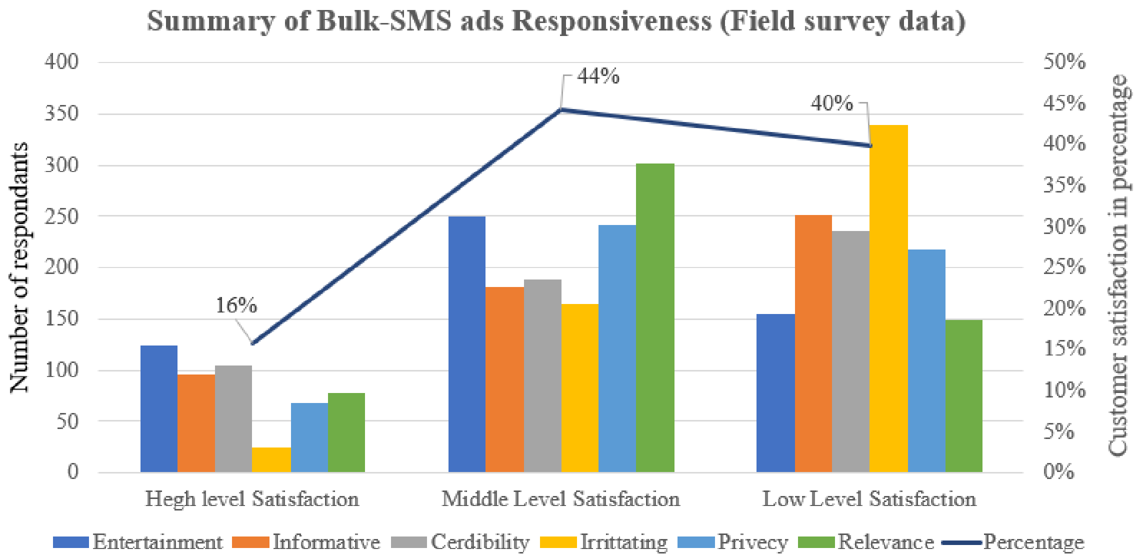

Figure 5.2.1: Summary of customer classification based on level of responsiveness

Furthermore, looking at detail's analysis of each factor of responses described in Table 5.2.1. There were four factors considered to be the main factors due to its' higher scored value relative to other factors, such as Informativeness, Credibility, Irritation, and Privacy based. More than 40% of the respondents strongly disagreed with all the questions discussed by these factors. Furthermore, 64% of the respondents strongly disagreed on the scale factors of "Irritation". This implies that SMS advertisements make people uncomfortable, annoying and disturbing with redundant alike messages.

The other 48% of the responses reflect that bulk-SMS ads are not informative and helpful, arrived timely, and some of the message contents do not understand easily.

Table 5.2.1: Details of Responses on Bulk SMS advertisement using survey data

Scale factors	Level of Satisfaction based on Number of Responses			
	High level Satisfaction	Medium Level Satisfaction	Low Level Satisfaction	Total
Entertaining	124 (23%)	250 (47%)	154 (29%)	528
Informative	96 (18%)	181 (34%)	251 (48%)	528
Credibility	104 (20%)	188 (36%)	236 (45%)	528
Irritation	24 (5%)	165 (31%)	339 (64%)	528
Privacy	68 (13%)	242 (46%)	218 (41%)	528
Relevancy	78 (15%)	301 (57%)	149 (28%)	528
Attitude	89 (17%)	310 (59%)	129 (24%)	528
Total	16%	44%	40%	

Credibility scored 45% of the responses laid on low-level stages, this implies that respondents did not trust bulk-SMS sources. In addition to these customers were reflected as there is a possibility to identify the senders from Ethio Telcom side. Permission-based SMS advertisements were supported by 41% of the respondents, because, these customers reflect that they need to be asked to receive any SMS advertisement and at the same time, they don't like to give any personal information to senders. This implies the current SMS advertisements are not permission-based.

5.3 DATA ANALYSIS FOR CDR DATA

Data analysis for CDR data considers each type of selected bulk-SMS advertisements numbers. The scale factors assessed in the field survey analysis are considered here partially. Factors like Entertaining, Informativeness, Irritating, and Relevancy were analyzed with a CDR data. As shown in Table 5.3.1 the maximum responses found in an Entertaining category specifically in SC_5 (sports-foot ball news) which is 34% among the dispatched of 55,454 messages have got responses.

The next best score in this group is SC_08 (Sport transfer news with different languages), it scores 23% of 4,264 sent messages. Lastly, SC_01 & SC_06 have scored 21% of 6,906 and 20% of 510 sent messages. These imply that customers are more responsive to entertaining types of SMS specifically in sports news & issues.

Table 5.3.1: Summary of bulk-SMS distribution among 10 short code numbers

Type of Bulk-SMS	Short-code Name	No of Customers	Received SMS	Replied SMS	Response in (%)
Entertaining	SC_05	11,396	55,454	18,692	34%
	SC_01	109	968	201	21%
	SC_07	33	510	53	10%
	SC_06	251	6,906	1,355	20%
	SC_08	323	4,264	983	23%
Info & Relev	SC_03	131	779	220	28%
	SC_02	129	838	190	23%
	SC_04	52	876	169	19%
	SC_09	155	7,642	814	11%
	SC_10	524	107,838	6,572	6%
Total		**13,103**	**186,075**	**29,249**	**16%**

Note: Info means Informativeness, Relev means Relevancy

In regard to informativeness and relevancy factors, SC_03 (Lifestyle advice from experts) were scored 28% of 779 messages which was best among its' category. The next SC_02(Vacancy information) was scored 23% of 838 dispatched SMS. SC_10 (DSTV service information) were scored the least among all.

Furthermore, a CDR data analysis part incorporates machine learning techniques in order to classify customers based on their level of responses. 'Weka 3.9.3' had taken to execute this work using three classifier algorithms, i.e. K-NN, MLP, and Naïve Bayes. A labeled CDR data were used by applying 10-fold cross-validation and percentage split test options. The summary of the performance evaluation result is shown in appendix Table A.5.1, and each metric was analyzed.

Accuracy

A labeled input data of 13,103 were used for an experiment. The number of actually labeled values for each class are 1,085, 4,353, and 7,665 for each category, such as High Level Responsive Customers (HLR), Medium Level Responsive Customers (MLR), and Low Level Responsive Customers (LLR) respectively. The accuracy of three algorithms to this data set is represented in Table A.5.1, such as 97.92%, 87.03%, and 75.12% for a k-nearest neighbor with 10-fold cross-validation, multilayer perceptron with a percentage split of 75%, and naive Bayes with a percentage split of 75% respectively. Therefore, the K-NN algorithm has performed the best accuracy rate by consuming less model building time as comparing with the other two algorithms.

Confusion Matrix Analysis

As per class recognition of each classifier shown in Table A.3, K-NN algorithm has got the best recognition for each class in two test options. As shown in Table A.5.1 the ratios of TPR and FPR of K-NN algorithm are 0.979, and 0.019 respectively. The second algorithm, MLP score the ratios of 0.870 and 0.137 as TPR and FPR respectively, finally of the Naïve Bayes algorithm are (TPR = 0.751, FPR = 0.319). Since K-NN algorithm returned the highest ratio close to 1 and the lowest ratio close to 0. The other two algorithms find a weakness in this test. As it has shown in the plotted ROC curves Figure A.4.2, the performance of K-NN algorithm has also performed best. Having the above all experiment results K-NN algorithm has selected.

5.4 RESULT OF CUSTOMER CLASSIFICATION USING CDR DATA

K-NN algorithm was selected through evaluation metrics shown in Table A.5.1. It consumed less time to build and evaluation with a cross validation test option than the other algorithms on this data set.

The number of correctly classified customers using K-NN, MLP, and Naïve Bayes algorithm are 12,830 (97%), 11,072 (84.5%), and 9,709 (74.1%) respectively. Thus, K-NN has performed best than the others. Therefore, K-nearest neighbor is the best classifier for this scenario. Customers are classified into three classes such as 1101 (9%) of the total as "High Level Responsive" with 96% of level of recognition; 7686 (59%) of the total subjected as "Medium Level Responsive" with 98% level of recognition, and the rest 4316 (32%) customers are categorized as "Low-Level Responsive" to bulk-SMS advertisements with 97% of level of recognition.

5.5 COMPARISON OF SURVEY VS CDR ANALYSIS

The final analysis result of a filed survey data and CDR data had taken to compare. This task may help to reinforce the reliability of filed survey findings. Finally, a survey analysis result indicated that there are 16%, 44%, and 40% of the data set are categorized to "High Level", "Medium Level", and "Low-Level" Responsive" customer respectively. Both results shown in Figure 5.5.1 tells that the majority of the customers are satisfied at a medium level, and a few portions of the customers had reflected as highly satisfied, and the rest of the customers are not satisfied on the services.

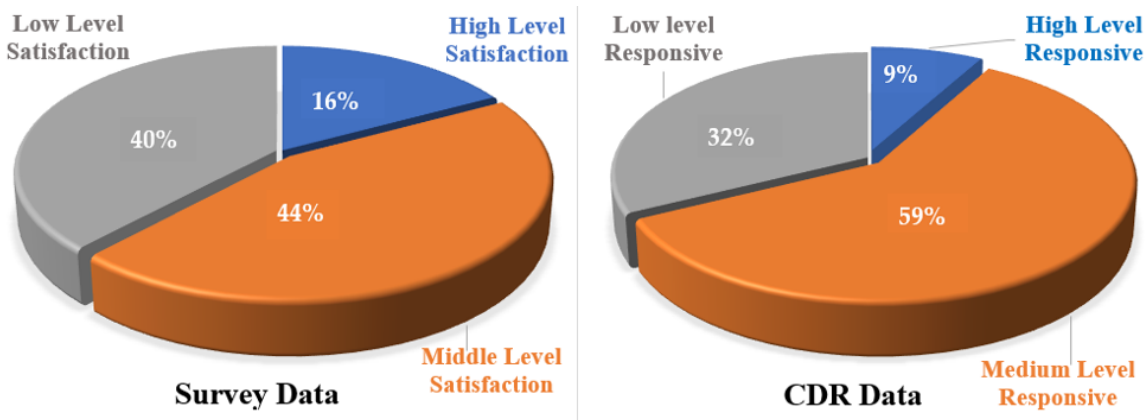

Figure 5.5.1: Summary of customer classification based on responsiveness analysis on bulk-SMS advertisements

6

CONCLUSION, RECOMMENDATIONS AND FUTURE WORK

6.1 CONCLUSION AND RECOMMENDATION

The aim of this research was to identify factors that influence customers' responsiveness attitude on bulk-SMS advertisements and classify customers based on the level of responsiveness. To make real this work, the thesis has used the mean method for statistical analysis of field survey data. In addition to this, a CDR data was categorized into three levels and analyzed by using an if-then, rules extracted from CDR data. Then three machine learning algorithms were applied to reinforce the finding using filed survey analysis. These algorithms are K-nearest neighbor, Multilayer perceptron, and Naive Bayes.

Data collections were applied in two ways, such as field survey and CDR data. From the field survey data collection, 528 customers gave responses among the distributed of 620 questionnaires. On the other hand, a large data set of bulk-SMS advertisement CDR data collected. That was a row CDR data of 1,475,708 received SMS and 168,325 replied SMS by the customers.

A field survey data was primarily tested for data normality, validity, and reliability & consistency using different statistical tests before applying detail analysis of data. After evaluating these tests, there are seven factors were considered to study how these factors affect customer responsiveness attitudes towards the bulk-SMS advertisement. As per the analysis result, only four scale factors had more influence on responsiveness attitude, i.e. informativeness, credibility, irritation, and permission-based or privacy. Therefore, these factors were taken as critical factors that affect customer behavior in bulk SMS advertisements to this context.

In addition to these, the field survey data had been further classified into three different levels based on customer responsiveness attitude using the mean method as shown in Section 5.2. According to the analysis results of field survey data, 16% of the total sample was categorized to customers with "High-Level Satisfaction", 44% of them was categorized to customers with "Medium Level Satisfaction", and the rest 40% of them was categorized in to customers with "Low-Level Satisfaction".

Coming to a CDR data, it was preprocessed via applying the required activities, such as data cleaning which means avoiding duplicates and handling missing values that makes noise while experiment and analysis. Attribute selection were conducted by looking its' relevancy to this specific study. Thus six attributes were selected manually such as mobile number, short-code number, call start time or deliver time (message sent date & time), write time (message received date & time), time span (time taken to respond to SMS), and location information.

In regard to a CDR data analysis, it is most likely important to select machine learning algorithms before applying. So that, this thesis had considered the performance of three algorithms such as k-nearest neighbor, multilayer perceptron, and naive Bayes using preprocessed CDR data.

According to the experiment results, the number of correctly classified customers using k-nearest neighbor, multilayer perceptron, and naïve Bayes algorithms are 12,830 (97%), 11,072 (84.5%), and 9,709 (74.1%) respectively among the total 13,103 customers. Due to its' higher performance among the other two algorithms, k-nearest neighbor classification scheme was selected in this scenario. Then a data set were classified into three classes i.e. "High Level Responsive", "Medium Level Responsive", and "Low-Level Responsive" customers with 9%, 59%, and 32% of the total respectively.

In addition to this, each short-code number further analyzed, and an entertaining type of bulk-SMS advertisements have got more responses than the others. Such as a bulk-SMS about sports news and discussion on transfer of foot-ball players have got 23% up to 34% among the total sent messages. Informativeness and relevancy types of bulk-SMS have got less response than entertaining. This tells that customers are most likely responsive to entertaining kind of messages.

This CDR data set analysis result will help to give a reinforcement on the results found via field survey analysis. As it is shown in Figure 5.2.1, the majority of the customers had classified as medium-level and low-level responsive customers to bulk-SMS advertisements in both cases. It can be concluded that most of the customers are not responsive or not satisfied with bulk-SMS advertisements.

Therefore, this thesis result will be considered as an input for marketing strategy improvement. Because it tells what a company should give more attention to improve bulk messaging services by considering all weak scale factors upon the test results. As per discussed in field survey data analysis, there are more work needs on factors that affect customers responsiveness attitudes towards bulk-SMS advertisement such as irritation, informativeness, credibility, and permission-based.

6.2 future work

In regard to future works, since a data set is taken for this work is not large enough, it is better to conduct such research with large size of data. The other vital issues that will be incorporated in future research are looking for the message reliability and content-wise study of these bulk-SMS will more maximize the service quality of experience at large and also it will help for customer identification with these concerns.

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A

APPENDIX

A.1 CORRELATION TEST RESULT FOR SURVEY DATA

Table A.1.1: Correlation test result for survey data

		ATTITUDE	Entertain	Informative	Credability	Irritating	Privacy	Relevance
ATTITUDE	Pearson Correlation	1	.238**	.247**	.224**	.901**	.188**	.410**
	Sig. (2-tailed)		.000	.000	.000	.000	.000	.000
	N	528	528	528	528	528	528	528
Entertain	Pearson Correlation	.238**	1	.411**	.169**	.326**	.207**	.214**
	Sig. (2-tailed)	.000		.000	.000	.000	.000	.000
	N	528	528	528	528	528	528	528
Informative	Pearson Correlation	.247**	.411**	1	.196**	.303**	.195**	.461**
	Sig. (2-tailed)	.000	.000		.000	.000	.000	.000
	N	528	528	528	528	528	528	528
Credability	Pearson Correlation	.224**	.169**	.196**	1	.179**	.185**	.305**
	Sig. (2-tailed)	.000	.000	.000		.000	.000	.000
	N	528	528	528	528	528	528	528
Irritating	Pearson Correlation	.901**	.326**	.303**	.179**	1	.233**	.471**
	Sig. (2-tailed)	.000	.000	.000	.000		.000	.000
	N	528	528	528	528	528	528	528
Privacy	Pearson Correlation	.188**	.207**	.195**	.185**	.233**	1	.309**
	Sig. (2-tailed)	.000	.000	.000	.000	.000		.000
	N	528	528	528	528	528	528	528
Relevance	Pearson Correlation	.410**	.214**	.461**	.305**	.471**	.309**	1
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	
	N	528	528	528	528	528	528	528

**. Correlation is significant at the 0.01 level (2-tailed).

A.2 RULE EXTRACTION

- Rule #_1: If a customer score more than 70% response among received SMS advertisement and its' time taken to respond on average for each SMS ads is less than 0.3, consider he/she as HLR.

- Rule #_2: If a customer score more than 70% response among received SMS advertisement and its' time taken to respond on average for each SMS ads is between 0.3 and 0.5, then consider this customer as HLR.
- Rule #_3: If a customer score more than 70% response among received SMS advertisement and its' time taken to respond on average for each SMS advertisement is greater than 0.5, then consider this customer as MLR.
- Rule #_4: If a customer score more than 50% response among received SMS advertisement and its' time taken to respond on average for each SMS ads is less than 0.3, then consider this customer as MLR.
- Rule #_5: If a customer score more than 50% response among received SMS advertisement and its' time taken to respond on average for each SMS ads is less than 0.5, then consider this customer as MLR.
- Rule #_6: If a customer score more than 50% response among received SMS ads and its' time taken to respond on average for each SMS ads is greater than 0.5, then consider he/she as LLR.
- Rule #_7: If a customer score less than 50% response among received SMS advertisement and its' time taken to respond on average for each SMS ads is less than 0.3, then consider this customer as as LLR.
- Rule #_8: If a customer score less than 50% response among received SMS advertisement and its' time taken to respond on average for each SMS ads is less than 0.5, then consider this customer as as LLR.
- Rule #_9 nine: If a customer score less than 50% response among received SMS advertisement and its' time taken to respond on average for each SMS ads is greater than 0.5, then consider this customer as LLR.

A.3 confusion matrix analysis

Table A.3.1: Confusion Matrix Analysis

Algorithms	Test option	Predicted classes	No. of TP	No. of FP	No. of TN	No. of FN	Recognition
K-NN	10-Fold CV	HLR	1046	55	11963	39	96.4%
		MLR	7539	147	5291	126	98.4%
		LLR	4245	71	8679	108	97.5%
	75% Split	HLR	254	13	2999	39	96.2%
		MLR	1861	42	1342	126	98.4%
		LLR	1088	18	2138	108	97.1%
MLP	10-Fold CV	HLR	499	124	11894	586	46.0%
		MLR	7156	1017	4421	509	93.4%
		LLR	3919	388	8362	434	90.0%
	75% Split	HLR	47	5	3007	217	17.8%
		MLR	1739	272	1112	153	91.9%
		LLR	1065	148	2008	55	95.1%
NB	10-Fold CV	HLR	899	972	11046	186	82.9%
		MLR	6218	2018	3420	1447	81.1%
		LLR	2519	477	8273	1834	57.9%
	75% Split	HLR	12	4	3008	252	4.5%
		MLR	1813	736	648	79	95.8%
		LLR	636	75	2081	484	56.8%

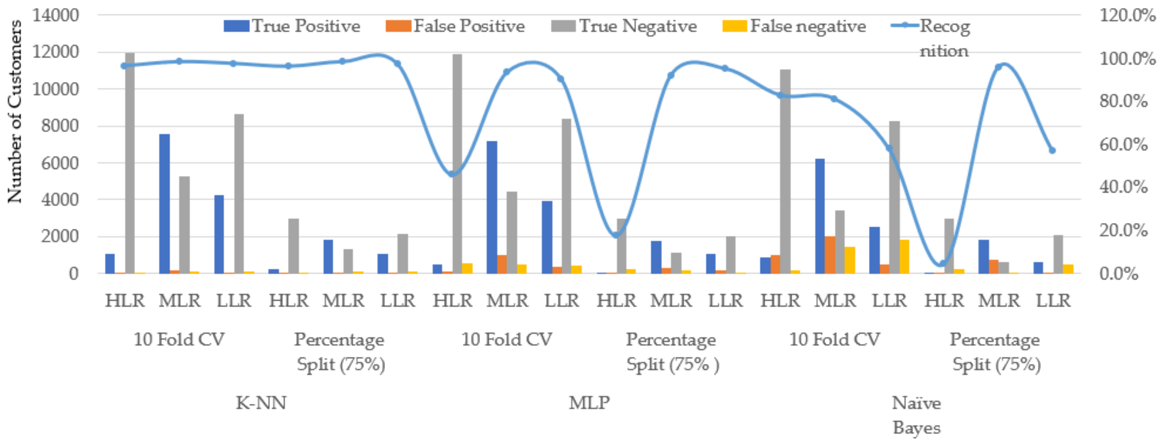

Figure A.3.1: Analysis of confusion matrix

A.4 ROC CURVE COMPARISON

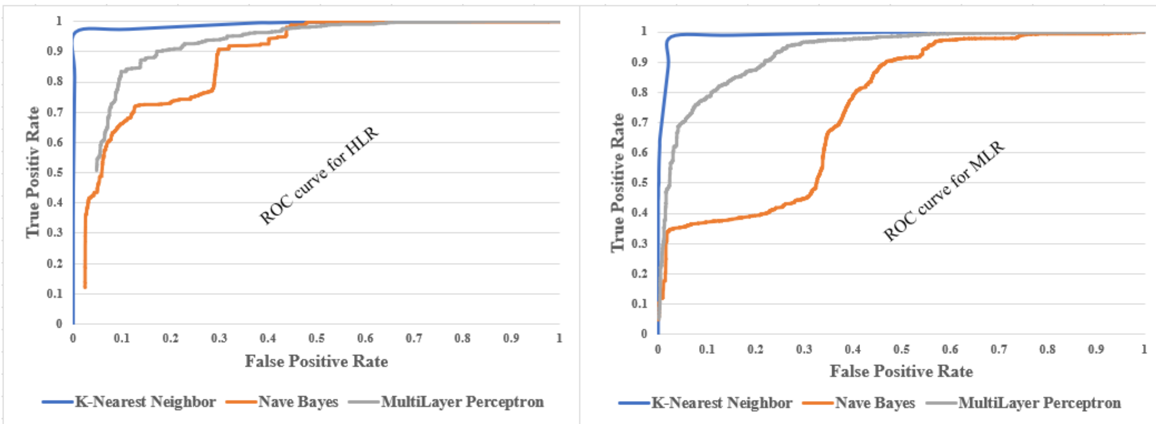

Figure A.4.1: Comparison of ROC curves

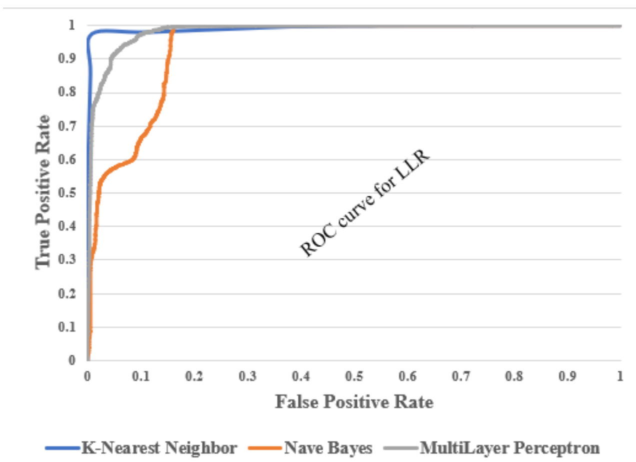

Figure A.4.2: Comparison of ROC curves

A.5 PERFORMANCE EVALUATION USING CONFUSION MATRIX

Table A.5.1: Performance using confusion matrix as discussed in section 3.4.7

Metrics	ALGORITHMS					
	K-NN		MLP		Naïve Bayes	
	CV	Split	CV	Split	CV	Split
Correctly Classified	12830	3203	11072	2851	9709	2461
Build Time	0.01	0.02	16.48	0.23	0.05	0.04
Evaluation Time	0.69	0.02	150.52	0.28	0.29	0.04
Sensitivity	0.979	0.978	0.845	0.87	0.741	0.83
Specificity	0.986	0.985	0.918	0.909	0.833	0.759
RMSE	0.118	0.122	0.261	0.249	0.359	0.354
F-Measure	0.979	0.978	0.84	0.851	0.725	0.716
ROC	0.991	0.991	0.947	0.963	0.822	0.83
Accuracy	97.92%	97.77%	84.50%	87.03%	74.10%	75.12%

A.6 CDR TABLE (SAMPLE)

Table A.6.1: CDR TABLE

No	Attributes	Description
1	CDR_ID	CDR Sequence Number
2	RE_ID	Service Identifier
3	BILLING_NBR	Billing Number

4	CDR_TYPE	Call type Id(The types of call 0: local call , 1: toll call within a charging area, 2: toll call between charging areas ,3: international toll call)
5	CALLING_NUMBER	Calling Number(call initiate number)
6	CALLED_NUMBER	Call destination number
7	CALLING_IMEI	International mobile equipment identity
8	CALLING_IMSI	IMSI of the calling party
9	THE_THIRD_PARTY_NUMBER	Third Party Number
10	CALL_START_TIME	the time when call start
11	CALL_END_TIME	the time when call end
12	CALL_DURATION	Call duration
13	CALL_FEE	the actual money deducted
14	CALLED_COUNTRY	called number country code of
15	CALLING_CARRIER	Calling carrier
17	CALLING_DISTRICT	Cell ID of the calling party
18	CALLED_DISTRICT	Cell ID of the called party
19	STATUS_DATE	Billing date
20	CALLING_SUB_ID	Calling subscriber ID
21	BILLING_CYCLE_ID	Billing cycle ID
22	CHARGE_1	Charge amount of you spend
23	CHARGE_2	Charge amount of you get disscount
24	RATE_ID1	Rate ID
25	ACCOUNT_ITEM_ID1	Account item ID
26	UPLOAD_TRAFFIC	Upload tra fficc