UNIVERSITY OF NAIROBI

SCHOOL OF COMPUTING AND INFORMATICS

A MODEL FOR ADOPTION OF CHATBOTS IN KENYA: A CASE STUDY OF ZUKU TELEGRAM BOT

By

ALEXANDER KARURI KAHIGA

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DECLARATION

I, Alexander Karuri Kahiga, do hereby declare that this research project report is entirely my own work and where there is contribution of other individual, it has been duly acknowledged. To the best of my knowledge, this research work has not been carried out before or previously presented in any educational institution for any award.

Signature: ____________________________ Date: ___________________________

Alexander Karuri Kahiga

P54/85800/2016

I, Dr. Elisha T. Opiyo Omulo, do hereby certify that this project report has been presented for examination with my approval as the University of Nairobi supervisor

Signature: ____________________________ Date: ___________________________

Dr. Elisha T. Opiyo Omulo

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ABSTRACT

The 21st century customers are tech savvy, and they expect a company's or business communication system to be seamless, real-time and customized. Social media has become a preferred tool of communication for connecting and bringing people closer despite the geographical and time boundaries that limited the traditional forms of communication. The use of the social media platform is also ideal for online chatbots. Due to the high social media presence both organizations and customers customer queries have increased the need for tools that will enable real-time and 24hours responses. The use of online chatbot is ideal and has significant benefits to an organization. However, chatbots adoption in companies is relatively a recent concept and there is limited literature specifically on chatbots adoption models or frameworks especially in Kenya. A survey was used to collect quantitative data from the customers. The data sample was then analyzed using factor analysis and multiple regression analysis. The study established that performance expectancy, effort expectancy, social influence and security were key determinants for chatbot adoption and were being moderated by age, gender and experience.

Key words: chatbot, model, adoption

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KEY DEFINITIONS

Model – this is a conceptual structure intended to serve as a guide for developing something that expands the structure into something useful.

Adoption – means to choose as a standard or required in a course.

Dependent variable – is a variable of primary interest to the study. It is also known as criterion of the study.

Independent variable – this is a variable that influences or determines the dependent variable.

LIST OF ABBREVIATION

UTAUT	Unified Theory of Acceptance and Use of Technology
TRA	Theory of Reasoned Action
SCT	Social Cognitive Theory
ALICE	Artificial Linguistic Internet Computer Entity
AIML	Artificial Intelligence Markup Language
MAS	Multi-Agent System
AI	Artificial Intelligence
IT	Information Technology
API	Application Program Interface
VIF	Variance Inflation Factor

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CHAPTER ONE: INTRODUCTION

1.1 Background

For businesses to be successful, they have to be where their customers or targeted audience are. The 21st century customers are savvy, and they expect a company's or business communication system to be seamless, real-time and customized in such a way that they will be able to get the right answers to their queries or find the products that they are looking for within a short time, or more specifically at a click of a button. Social media has become a preferred tool of communication for connecting and bringing people closer despite geographical and time boundaries that limited the traditional forms of communication. It is also popular- Facebook Messenger alone is estimated to have more than 1.2 billion monthly users. Companies around the world are taking advantage of the use of the social media platforms such as Facebook, Twitter, WhatsApp, and Telegram to reach out to their customers and constantly interact with them at a very low budget.

The social networks help companies to have a better understanding of their target audience, facilitate better communication and increase their engagement. Today, a majority of businesses are building and reinforcing relationships with their customers through their social media networks. It has also ensured that the communication between the companies and their customers is two-way, and they (the customers) are not only providing their feedback, but also sharing their ideas and suggestions on how companies can improve their communication strategies, products and services to suit the consumers' needs.

Companies are witnessing the benefits of reaching their target audience, regularly interacting with them and creating a community that thrives on communication being in real-time, engaging, fluid and works both ways. It has enabled dialogues and discussions to take place between consumers and representatives of a company, something that was not possible when businesses were using the traditional media platforms. In addition to that, a company is able to gauge or assess the effectiveness of their messages based on the feedback (likes and re-posting) and comments of the organization's posts. Based on the customers' reaction, a company will be able to determine on how it can make their products and services become more suitable to their consumers and not guess or assume their needs as was the case before the introduction and popularity of the social media platforms. In addition to that, the way the customers feel and think towards a certain organization will influence its public perception, and in the end determine the success or failure of a company.

The use of the social media platform is also ideal for online chatbots. The virtual chatbots are able to imitate human conversations, and therefore help a company to save time and effort through the automation of their customer support. According to the Gartner forecasts, it is expected that by 2020, approximately over 85% of customer interactions will be handled with virtual chatbots. However, it is important to point out that chatbots can be able to fulfill other tasks other than providing responses to customers' inquiries. For instance, they can be used to collect information about users, help businesses (especially SMEs) to effectively organize their meetings and reduce the overhead costs of a business.

1.2 Statement of Problem

In the past companies primarily relied on their strategic advertisements to attract their target customers and experienced a ton of success, today they have to do more to receive a similar level of success. The 21^{st} century customer is technological savvy and used to receiving information in real-time. Large companies with high volume customer interactions have a large number of these queries. Therefore, there is need for successful deployment of tools that will enable their questions to be answered in real-time and offer 24 hours' responses in a cost effective way. Employing a round the clock customer support staff that will effectively handle thousands, if not millions of customers queries on a daily basis is not only hectic but it is expensive. Most organizations do not want additional expenses in terms of salaries and infrastructure (buying or renting office space, office equipment etc.)

The use of the social media platform is also ideal for online chatbots and has significant benefits to an organization. However, chatbots adoption in companies is relatively a recent concept and there is limited literature specifically on chatbots adoption models or frameworks especially in Kenya. In this study, Zuku company was selected and in particular its customers who have installed Zuku Fiber to determine if they had used the company's chatbot for communication purposes and queries resolution. The interest of the study was to assess their overall experience such as how they felt about its performance, overall security and how these factors influenced them in terms of making the chatbot their main mode of communication with their service provider (in this case Zuku).

1.3 Purpose of the Study

The broad objective of this study is to propose an ICT model for adoption of chatbots in Kenya for companies with high volume customer interactions.

1.4 Objectives

1. To determine key technological and social factors that influence adoption and use of chatbots in Kenya.
2. To develop a model that will be used as blueprint for the adoption and use of chatbots in Kenya
3. Use survey method, test the validity and viability of the proposed model.

1.5 Research Questions

1. What are the technological and social factors that influence the adoption and use of chatbots in?
2. What are the constraints that need to be taken into consideration when designing a framework for the adoption of chatbots?
3. What are the best methods to use to test the validity and viability of the proposed model?

1.6 Significance of the Study

The implementation of chatbots in the messaging platform, which are used by a majority of people today, creates an opportunity for companies that want to interact in a one-on-one conversation with their users. The advent of new technologies has revolutionized the way people interact with each other and with companies. The integration of messaging apps allows customers to chat with bots, ask questions, and receive answers within a short duration and also appropriate recommendations. Chatbots are considered to be useful for companies to be able to automate customer service replies and interact with customers in real-time. This will enhance the communication between customers and companies that they purchase different products and services. This research will be of significance to organizations that offer customer service in various platforms such as banks, insurance, airlines and consulting industries.

1.7 Scope of the Study

The study focuses on the adoption of chatbots by companies in Kenya. The research was focused on organizations that are currently using Telegram chatbots to fulfill certain activities in their companies. It also addressed the reasons why the adoption of chatbots in Kenya is occurring at a slower pace than is the case in the developed nations. In this regard, the study identified the challenges that organizations are facing in trying to integrate chatbots in their company operations. The study also highlighted the benefits of using chatbots for service industry companies and the future directions of this technology.

CHAPTER TWO: LITERATURE REVIEW

2.0 History and Evolution of Chatbots

The concept of chatbots was laid by Alan Turing when he developed the Turing test in 1950. He believed in the future, humans would develop highly intelligent machines whose text-only conversations will be indistinguishable from that of other human beings. The first Chatbot to be developed was Eliza in 1966 by an MIT professor called Joseph Weizenbaum. The chatbot took the form of a psychotherapist and was able to respond to the user with questions by matching their prompts to scripted responses. Initially, it was able to pass the Turing artificial intelligence test. It was able to recognize cue words or phrases in its input, and its output was a set of pre-programmed responses in relation to its input. It, therefore, created an illusion that it understood the information that was being provided. Another chatbot that was developed using this technology was Parry (1972).

Recent notable programs include Artificial Linguistic Internet Computer Entity (ALICE) (1995), Smarter-Child (2001), IBM's Watson (2006), SIRI (2010), Google Now (2012), ALEXA (2015), Cortana (2015) and Bots for Messenger (2016). The ALICE chatbot was revolutionary because of its ability to use natural language process, which enabled it to have a more sophisticated form of communication in comparison to ELIZA, and its open-source nature, which allowed developers to use the AIML (artificial intelligence markup language) to create their own chatbots that were powered by ALICE.

Initially, Chatbots were developed for standalone applications such as being conversation partners to their users as was the case for ELIZA, and ALICE. As technology and information on chatbots advanced, developers began to realize that they could develop chatbots that fulfill other functions other than conversing. In 2001, the SmarterChild chatbot was launched. This chatbot introduced Neuro-linguistic programming to the SMS network and successfully performed a wide variety of tasks such as providing news, weather, sports score, and stock information. Later on, in 2009, the Chinese messaging giant, WeChat was launched with the help of the chatbot support. This chatting service made it easier for developers to build native bots that were compatible with it, which led to a surge of chatbots being developed to be used on WeChat. A majority of these developers created chatbots that could fulfill the functions of chatting (conversing), and provide recommendations for products that people could buy. The strategy was borne out of the culture of a majority of Chinese shoppers relying on recommendations from their friends and relatives to influence their purchases. It resulted in the boom of commerce in this region, and the promotional chatbots led to the development of modern era chatbots.

Siri was the first mainstream assistant that was developed in 2010. It allowed mobile users of Apple to interact via text or voice, which allowed for a majority of the tasks to be completed via the natural language. This technology was able to interact with the apps that users had installed on their devices. This led to the development of Google Assistant in 2012, Cortana for Microsoft, and Amazon's Alexa in 2015. During this period (2012-2015) chatbots mainly flourished in less popular messaging platforms such as Telegram and Slack. It was not until 2016 that social media platforms such as Facebook began to use chatbots- API for its messaging platform. It contributed to a corporate craze for the development of chatbots.

Most of the available chatbots today such as Bots for Messenger have additional functional features such as web searching abilities, which has enhanced their communication capability with humans and therefore made them more effective from a business point of view. Today, a majority of the companies' chatbots run via messaging apps such as Facebook Messenger, WeChat, WhatsApp, LiveChat, Kik, Slack, Telegram and SMS. They are used for different business needs such as Business to Customer services, sales, and marketing.

As of 2016, Facebook Messenger has allowed its developers to integrate chatbots on their platform. It led to the creation of approximately 30,000 bots for Facebook Messenger in the first six months. As of September 2017, there were 100,000 chatbots that had been integrated on the Facebook Messenger by different developers. The bots mainly appear as individual user contacts but can act as participants in a group chat. Companies in different sectors are seeing the need to incorporate chatbots. Banks, insurers, airlines, hotel chains, restaurant chains, government entities, and health care providers are increasingly using chatbots to answer simple questions, for promotion purposes, and increasing overall customer engagement. In a study by Business Insider Intelligence (2016) illustrated that 80% of businesses intended to have implemented the use of chatbots by 2020. In another study by Capan (2017), it showed that 4% of companies are using chatbots to run certain aspects of their companies.

2.1 History and Evolution of the Telegram

Telegram is a cloud-based instant messaging and voice over IP service that is available on Android, iOS, Windows Phone, Windows NT, macOS, and Linux. It allows its users to send messages and exchange any type of files that contain audio, video, and photos. While the client-side code is open-source software, its server-side is closed-source and proprietary. It is important to note that the services provide APIs to independent developers. For security purposes, the messages and media transferred by clients in the Telegram platform are client-server encrypted. The voice calls have an end-to-end encryption, and there are an optional end-to-end encrypted ‘secret’ chats between two online users. However, this security feature does not exist in group chats.

The Telegram platform was launched in 2013 by Nikolai and Pavel Durov. In the year that it was launched, Telegram reported that it had approximately 100,000 daily active users. By 2014, the company announced that it had 50 million users who were generating 1 billion daily messages, and it estimated that it had approximately 1 million new users that were signing up to use the services that are provided on a weekly basis. In the first five months of 2015, the traffic to this social media platform doubled, generating approximately 2 billion daily messages. In March 2018, Telegram announced that it had reached 200 million monthly active users.

2.2 Chabot as agents and Multi-Agent System (MAS)

According to Imran (2015) a chatbot is a type of conversational agent, which has been designed to simulate an intelligent conversation with human users through either auditory or textual methods. Imran further notes that computer-based natural language processing is a key feature of a chatbot. It is also important to point out that chatbots provide a viable interface between a computer and human user with intelligent features. There are two types of chatbots: chatbots that function based on the rules that have been set, and chatbots, which function based on Artificial Intelligence (AI). Chatbots that are built to use rules are limited because, they are only as 'smart' as the way they are programmed. AI based chatbots provide the impression that they are intelligent, because they are able to understand natural language, do not rely on pre-defined commands, and they possess the ability to get 'smarter' as they interact more with humans. This is due to their ability to maintain states. Example of chatbots that use natural language processing include: Google Assistant, Microsoft Cortana, Apple Siri, and Amazon Alexa.

Rzevski and Skobelev (2014) notes that multi-agent system (MAS) technology is a modern software technology that is used for complex applications. Multi-agent chatbot systems have additional built-in features such as pro-activity, autonomy, and social ability. The addition of these features is used to enhance intelligent performances of the chatbot systems. Rzevski and Skobelev (2014) notes that a majority of the multi-agent systems are large networks comprised of small agents that are running in a parallel manner. Therefore, the performance of the multi-agent systems will depend on the design and capability of these agents.

2.3 Related works

Shawar and Atwell (2007) notes that initially chatbots were developed for the purposes of entertainment and to mimic human conversations. Today, technology has enabled developers to build chatbots that can perform a wide range of activities such as retrieving information, answer questions, shopping assistant, language partner, perform customer-based services, and assist students in their education. Brynjolfsson and McAfee (2017) highlight that for people to have a better understanding of the role and capability of chatbots in the modern society, they have to reflect on automation and humans' relation to technology. These researchers add that a majority of humans' daily interaction are facilitated by complex and autonomous technology. Hoff and Bashir (2014) notes that a majority of tasks and responsibilities that were previously done by human beings have been replaced by automated systems. Wickens et al. (2013) notes that automation has led to a wide range of benefits such as comfort, job satisfaction and improved safety. Venkatesh (2003) notes that while the right technology may improve the overall productivity of an organization, when these machines fail they can contribute to undesirable consequences such as substantial financial losses for a company.

Frey and Osborne (2013) notes that the development of chatbots has been facilitated by the advancement of algorithms that allow previously perceived cognitive tasks to be automated. Brynjolfsson and McAfee (2017) notes that machine learning and AI have enabled chatbots to perform tasks that were previously deemed to require human judgment such as customer services. Brynjolfsson and McAfee (2017) continues to note that machine learning is similar to the human mode of learning, and it is the reason why performance of systems that are based on machine learning are compared to human performances.

Murgia et al. (2016) argues that human-chatbot interaction in future will be an essential domain in specific knowledge sharing, for instance as is the case in the question and answer websites. Portela and Granell-Canut (2017) notes that the integration of AI and machine learning in chatbots has increased their capabilities and potential. It is the reason why they are a standard feature on smartphones and web interfaces. Dale (2016) adds that these features have allowed chatbots to be integrated into messaging platforms such as Facebook Messenger and WeChat as a way for service providers to easily and widely reach out to their customers. Accenture (2016) notes that customer service is a domain whereby chatbots are receiving growing interest. This technology is being used to offer customer service in various platforms such as banks, insurance, consulting and industry. Crutzen *et al.* (2011) notes that humanlike conversation of chatbots provides customers with the opportunity to type questions and get meaningful answers to their questions that is provided by chatbots.

Even though chatbot technology has led to machines engaging humans in different capacities such as customer service, do humans trust these applications that they consult with on a regular basis? Hoff and Bashir (2014) noted that there are parallels between human interpersonal trust and trust in automation. Lee and See (2004) noted that human trust is different from machine trust because machines lack things such as intentionality, loyalty, and values that are critical to the development of trust between human partners.

Technologies that were once referred to as ‘emerging,’ and which were met by a lot of skepticism such as cloud computing, mobile banking and the block-chain technology are today considered innovations that are required by companies in different sectors for survival, increasing their competitive advantage and maintaining overall organization success. It is important to point out that while these destructive technologies have been shown to be beneficial to the organizations that have adopted such as mobile banking has reduced the need of a majority of customers to go and queue in the banking halls to access a majority of the services, there has always been the issue of security in terms of protecting the customer from being hacked or his or her information being accessed by third parties. Ismail (2018) noted that, despite the fact that innovative technologies in the 21st century are influencing business models and customer interactions, 70% of the UK business leaders have admitted that they are concerned with their organization's ability to adopt to the new technology. In another study by Index (2017), it noted that 48% of the business leaders had not increased their IT budgets in 2017. Zumstein and Hundertmark (2017) pointed out that although chatbots have a lot of potential benefits as an emerging technology, one of the threats that can have an impact on its adoption by a majority of companies is protecting both the providers and users data. The researchers pointed out that is companies offer stand-alone chatbot applications, then they will be responsible for protecting and handling customers' data. Alternatively, they can offer chatbot on third-party platform whereby data is sent to social media networks such as Facebook, WeChat and Whatsapp, which have authentication measures that protect data access from unauthorized parties. The researchers recommend that chatbot developers and operators should take punitive measures for both data privacy and protection.

While these studies focus on the lack of ability of chatbots or machines to develop trust and security risks, in this study it will assess how chatbots despite their 'perceived short-comings' (lack of trust and security) can be used to improve company-customer communication in Kenya.

The study will investigate how other factors such as the performance and security capabilities of chatbots can enhance the communication between companies and their customers.

2.4 Chatbots Adoption Models

The adoption by users of new technology can be explained using a variety of factors that are inter-related. There are different models that have been designed to provide an understanding of why people are willingly ready to use and adapt to new technology. In this section, it will discuss four models: Unified Theory of Acceptance and Use of Technology, Theory of Reasoned Action, Social Cognitive Theory and Technology Acceptance Model.

2.4.1 Unified Theory of Acceptance and Use of Technology (UTAUT)

In this theory, it postulates that there are four constructs that determine user acceptance and usage behavior of a new technology. These are: performance expectancy, effort expectancy, social influence, and facilitating conditions. The constructs are influenced by age, gender, experience and voluntariness of use, which determine user acceptance and behavior. The influence of performance expectancy of behavioral intention is influenced by age and gender such that its effect is higher in young men than any other group. On the other hand, influence of effort expectancy on behavioral expectancy is influenced by age, gender, and experience, and its effect is higher on young women at their early stages of experience. The influence of social influence on behavioral intention is affected by age, gender, experience and voluntariness, and it is higher on older women using mandatory settings in the early stages of experience. Figure 2.1 below is an illustration of the UTAUT model.

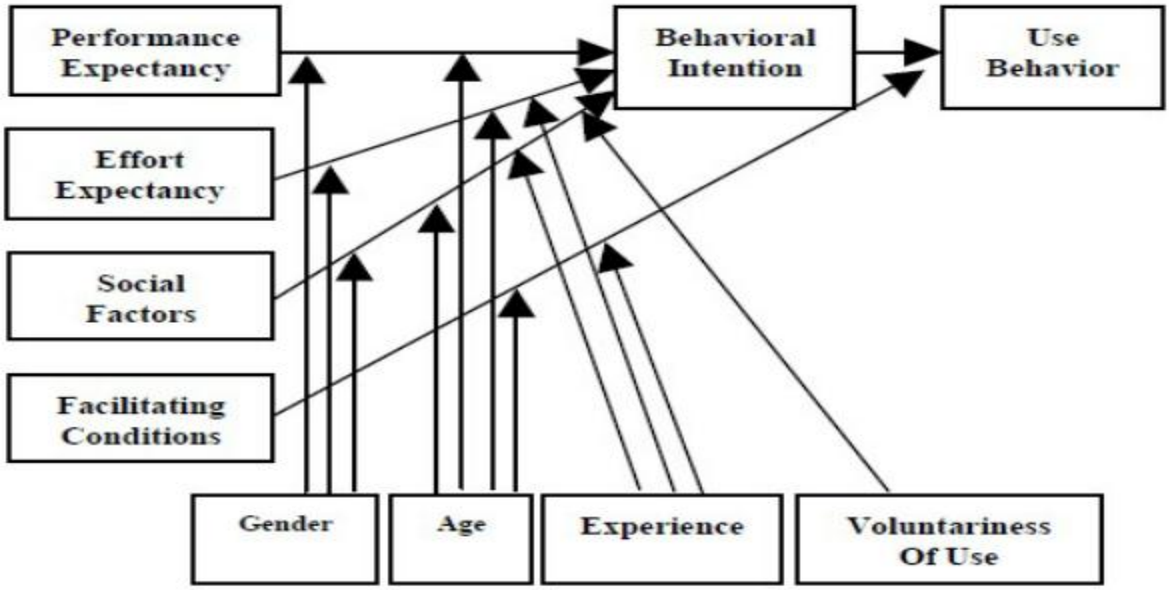

Figure 2.1: UTAUT Model Source: Venkatesh *et al*. (2003)

2.4.2 Theory of Reasoned Action (TRA)

According to this theory an individual's behavior is influenced by his or her intention to exhibit such behavior, which is driven by an individual's attitude towards a certain act, or behavior. Applied to the aspect of the use of chatbots for customer services, people would accept interacting with them based on the positive benefits that are associated with using this technology. However, this theory fails to take into consideration other factors such as fascination of the new technology, performance expectancy, effort expectancy and cost. Figure 2.2 below provides an illustration of the TRA model.

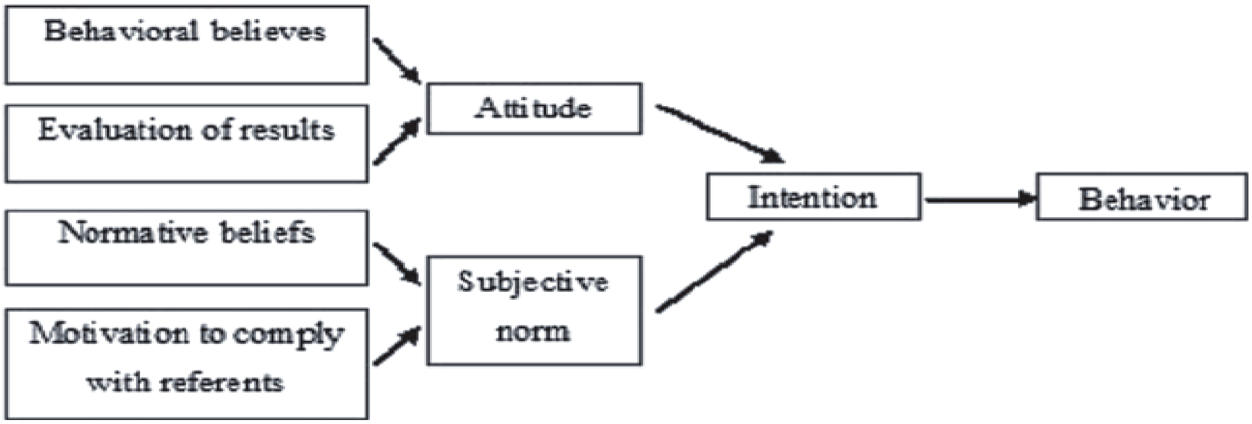

Figure 2.2: TRA Model

Source: Fishbien *et al.* (1980)

2.4.3 Social Cognitive Theory

In this theory it postulates that an individual's action are influenced by his or her own behavior, personal convictions and the environment, which operate independent of each other. Figure 3 below provides an illustration of the SCT model.

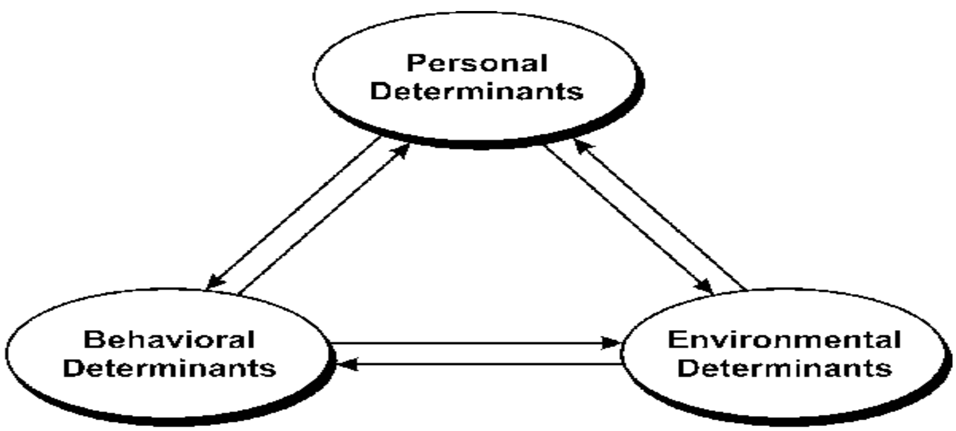

Figure 2.3: SCT Model

2.4.3 Technology Acceptance Model (TAM)

Technology Acceptance Model (TAM) and - suggests that when a user is presented with a new technology, a number of factors influence their decision regarding how and when they will use it. This includes its perceived usefulness and its perceived ease of use. Technology acceptance model, which was also developed from theory of reasoned action, focuses on the attitudinal explanation of intention to use a specific technology or service.

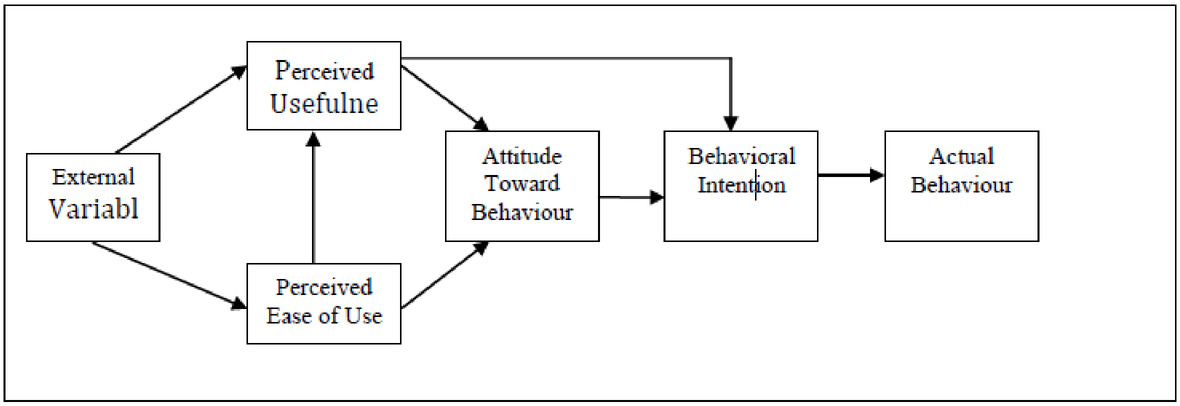

Figure 2.4: Technology Acceptance Model

Source: Bagozzi et Warshaw (1989)

2.4.4 Summary of the Gaps in the Reviewed Adoption models

This chapter has discussed and presented the technology acceptance theories and models however, some of the shortfall associated with their use in determining the adoption drivers of chatbots are summarized in the table below:

Table 2.1: Summary of the Models Gaps

Model	Gap
The Theory of Reasoned Action (TRA)	This is a theory driven framework, which everything is perceived as an attitude or a norm towards acceptance of technology. The theory assumes to match technology and user's attitude yet so many factors can influence a user's attitude towards technology.
Social Cognitive Theory	Social cognitive theory is so broad and it has been criticized for lacking any one unifying principle or structure.

Technology Acceptance Model (TAM)	The model does not account for the influence and personal control factors behavior. Other factors such as economic factors, outside influences from suppliers, customers and competitors are also not considered by the model.
Unified Theory of Acceptance and Use of Technology	Fails to address the issue of security & privacy concern which is a key factor in the adoption of the chatbots.

2.5 Conceptual Framework

The study identified five elements or factors that he investigated in relation to how Kenyan customers feel about companies using chatbots to perform customer service duties that were previously handled by humans. These factors are:

- Performance Expectancy: It refers to degree in which the stakeholders (customers and company executives) believe that using chatbots will improve the communication efficiency between the company and their customers in terms of response time and solving their problems.
- Effort Expectancy: Refers to the degree of ease for the customers interacting with these chatbots
- Social Influence: The perception that customers will have in terms of using these chatbots as a result of previous use by their family members and friends.
- Facilitating Conditions: This factor attributes to the cost of implementation, and compatibility with the customers' present mode of communication.
- Security: While using an innovative technology there is always a risk related to the data that this innovation could collect and use. In the case of chatbots, users' concerns are related to the fact that as those chatbots are extremely intelligence, they could also use their response to record their replies and profile them. Moreover, as it is also possible to

use chatbots for payments, security and privacy are two big obstacles towards chatbots adoption

Having identified all these factors, the study came up with the conceptual framework depicted on figure 5.

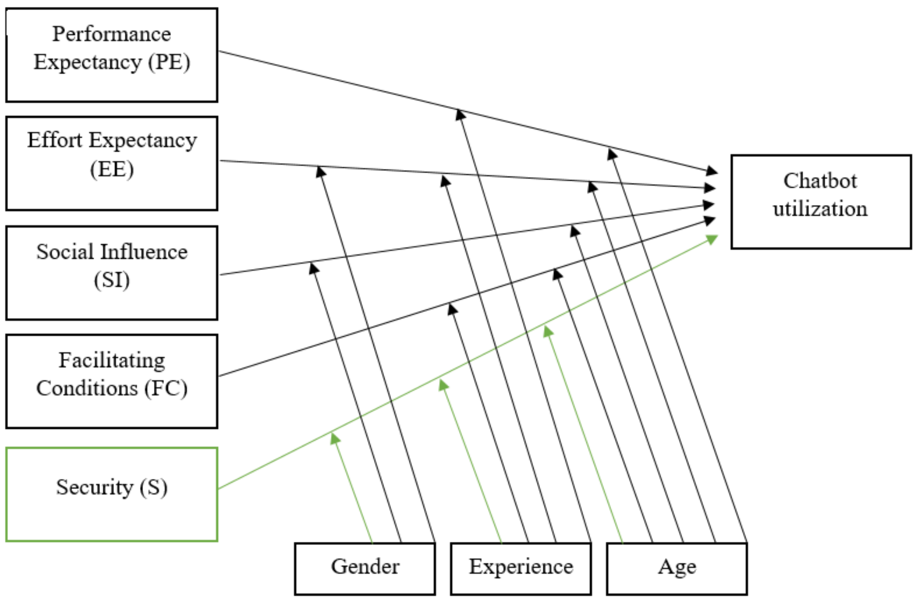

Figure 2.5: Conceptual Framework

Source: Author

2.6 Research Hypotheses

H1: Age and experience will moderate the effect of performance on chatbot utilization such that it will have a stronger impact on the older (50+ years) than in the younger generation (less than 50 years) during the early stages of interaction with the Zuku chatbot.

H2: Age, gender and experience will moderate the effect of effort expectancy (ease of use) on chatbot utilization such that it will have a stronger impact among older (50+ years) than in the younger women during the early stages of interaction with the Zuku chatbot.

H3: Age and gender will moderate the effect on the social influence of chatbot utilization such that it will have a stronger impact on young women, than in young men who are using it as a communication tool with the Zuku firm.

H4: Age and experience will moderate the effect of facilitating conditions (e.g. compatibility with the user's mode of communication) on chatbot utilization such that the effect will be stronger among older- than the younger-generation in the early stages of interaction with the Zuku chatbot.

H5: Age, gender and experience will moderate the effect of security (privacy) on chatbot utilization such that the effects will be strongest among older women than in any other group that will be studied in the early stages of experience with chatbot utilization

2.7 Conclusion

The chapter has reviewed diverse literature sources elaborating on chatbots adoption, and history developments done in this field. Further, it has developed a conceptual framework to guide the actual study.

CHAPTER THREE: METHODOLOGY

3.1 Introduction

This chapter outlines the approach the study adopted in carrying out this study. It defines the research design, data collection methods, research procedures and data analysis methods.

3.2 Research Philosophy

The aim of this research was to propose an ICT model that can lead to the adoption of chatbots in Kenya for companies that have a relative high volume of customer interactions. The study implemented an appropriate research philosophy, which built the foundation for the overall research design. It is important to note that the research philosophy that was adopted for this research is Positivism. In positivism, it denotes that social reality is a phenomenon that can be observed, achieving factual knowledge in regard to whether the adoption of chatbots in companies that have high interaction rates with their customers on various issues is plausible in Kenya. This was achieved through data collection, analysis and interpretation of the results that were collected for this study. The study also took an independent position to get positive results. The research aimed to derive knowledge from measurable facts.

3.3 Research Design

Cooper and Schindler (2014) defines research design as a blueprint to a research process. It provides the readers with the framework of how the research was conducted and guidelines on how they can replicate it to get similar results in future. It provides a description of the process that the researcher undertook during the study in the sample selection approach, data collection instruments and research procedures that were implemented. Cox and Hassard (2010) defines it as an appropriate structure in which a specific research is implemented. This study used a descriptive research design framework. The research employed the use of analysis and description phenomena techniques from unexplained assumptions to achieve maximum intuitive presentations. Saunders *et al.* (2009) states that a descriptive research design documents a specific study phenomenon in its real situation without having to worry that a research investigator will interfere and therefore influence the results of the study.

3.4 Target Population

Cooper and Schindler (2014) defines a population as a group consisting of total collection of the elements that the study aims to study. The study focused on Zuku customers that are currently using chatbots to interact with the company.

3.5 Sampling Design

Saunders et al. (2009) defines a sampling design as the technique that the researchers use to select a sub-group from the total population that will be involved in a study. It acts as a framework to assist the researcher to determine how the study samples will be selected from the study population.

Purposive sampling approach was used in this study. It is a non-random sampling approach whereby the members of the target population who meet some specific criteria such as in this case Zuku fiber installation in their house, or business premise were targeted to participate in this study. This means that the study involved visiting these homes and business premises and convincing the owners to participate in this study after explaining to them the purpose of the study.

3.5.1 Sample Size

Cooper and Schindler (2014) defines a sample size as a group of respondents who are part of an overall target population that was selected carefully to represent a population. A sample size allows a researcher to draw valid conclusions on the research objectives that were formulated at the start of the study. To determine the ideal sample size for this study used the following formula:

$no=Z^2 * \sigma^2/e^2$

whereby: no= sample size e= Level of precision

z= Value of Z in a normal distribution curve

σ^2 = Variance of an attribute in the population

$Z= 1.64$, $\sigma^2= 9.65$, $e= 1$

$1.64*8.65/1^2= 122.46 = 122$ (as it involves people)

In this study, 120 research participants were selected and would be an ideal sample size to collect the required data for this study. The reason for this is that Zuku has a limited network coverage and this means that it is only available in specific areas in Nairobi which is the area the study focused on during the data collection process.

3.6 Sources of Data

There are two sources of data that a researcher can use in a dissertation- primary and secondary sources. A primary source is defined as any data or information that a researcher collects first hand from his or her sources, mainly the research participants. This data has not been published. However, it is important to note that the data or information is considered as authentic, reliable and objective because study used effective tools to collect, store and analyze the data. On the other hand, secondary source is any form of information that has already been collected recorded and reported by previous researchers. It can be accessed from a variety of sources such as scholarly journals, published electronic sources and computerized databases. In this study, the study used primary sources and data was collected using questionnaires.

3.7 Data Collection Method

The study used questionnaires for data collection purposes. Questionnaires are defined as a list of questions that a researcher develops, which the respondents are supposed to provide relevant answers in a truthful and non-biased manner. It was a structured questionnaire that had a 5-point Likert scale.

After the successful recruitment of the respondents for the quantitative process, the questionnaires were distributed through their e-mails, and through the social media (WhatsApp and Telegram). The respondents were contacted via a call/text to ensure that they were aware that an email or message containing the questionnaire has been sent to them and their expected submission date.

3.8 Data Analysis

It is defined as the processes that a researcher employs to bring order, structure and meaning to the information that was collected during the research. Descriptive statistics were used for the data that was collected using the questionnaires. The study used different strategies such as frequencies, mean, standard deviation, inferential statistics and multiple regression to analyze the data.

3.9 Ethical Consideration

The research applies specific ethical guidelines to ensure and assure that all the research participants were not at any point of time during the research exposed to any form of harm that may affect or ruin their reputation and careers. The study had to protect the identity of all the research participants. This means that even though the respondents provided personal details, there is no section where they were required to write their names or any form of information that could be used to identify them personally. Secondly, only the researcher had access to the questionnaires and email information. There is no third party who had access to this information. These drastic steps ensured that the identity of the research participants was not revealed during and after the research process.

The study was also keen on not fabricating or falsifying the data that was used in the research. It was also important to note that copyright guidelines were observed and all authors whose work is quoted in this thesis was credited using the right APA formats for in-text citations and reference page. It was also important for the study to observe ethical behavior and promote a sense of trust between him and the participants during the data collection process. This was achieved through being honest on the subject and purpose of the study.

CHAPTER FOUR: RESULTS AND DISCUSSION

4.1 Chapter Introduction

The chapter presents the results collected in the study and the analysis of the data. The chapter covers demographic and descriptive analysis of the data, reliability analysis, factor analysis and finally the last section tests the hypotheses identified at the onset of the study.

4.2 Overview of Data Collection and Analysis

The survey of this study was sent on January 25th 2019 via email and social media platforms (Facebook, WhatsApp and Telegram) and door to door visits during a timeframe of 30 days, and collected on the submission date of 25th February 2019 for data analysis purposes. However, out of the 120 research participants, 33 failed to submit the questionnaires within the set timeframe, and therefore their responses were automatically excluded from the data analysis process. All the data was gathered, filtered, and cleaned using the Microsoft Excel to identify and exclude the questionnaires that were either incomplete, or had been filled twice in some or all of the questions. After the cleaning and filtering process, the author had 77 questionnaires that were used for data analysis purposes.

All the questions were designed using a Likert scale. The answers that were provided using the Likert scale were converted using the numerical scale where ‘1’ refers to ‘strongly disagree,’ and ‘5’ refers to ‘strongly agree.’ The reason behind using numerical values to answer the set questions is to enable the author to calculate the arithmetic mean that he can use to have a better understanding of how the data was distributed.

4.3 Descriptive Analysis Results

This section provides the demographic characteristics of the respondents of this study. Table 4.1 provides an illustration of the gender distribution of the respondents of this study.

Table 4.1: Gender Distribution of the Respondents

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	F	34	44.2	44.2	44.2
	M	43	55.8	55.8	100.0
	Total	77	100.0	100.0	

Source: Research Data 2019

Information in table 4.1 shows that there were 34 (44.2%) females and 43 (55.8%) male respondents that took part in this study. The total number of participants who were involved in this study was 77. Figure 4.1 provides a visual illustration of the males and females that took part in this study:

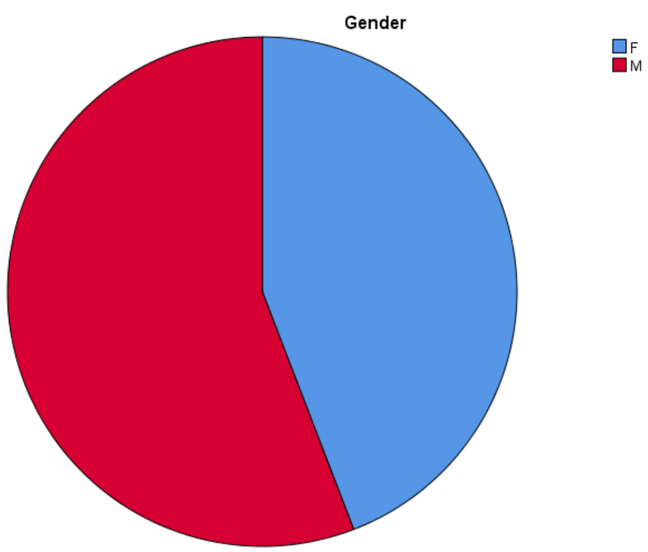

Figure 4.1: Gender Distribution

Source: Research data 2019

The research was also keen to assess the age distribution and education level of the research participants as part of having a better understanding of the demographics of the respondents. Information on age distribution is presented in table 4.2 below.

Table 4.2: Age Distribution of the Research Participants

		Frequency	Percent
Valid	<18	1	1.2987
	19-29	24	31.169
	30-39	34	44.156
	40-49	12	15.584
	>50	6	7.792
	Total	77	100.0

The majority of the respondents that participated in this study belonged to the 30-39 (34) and 19-29 (24) age groups. The least number of participants belonged to the <18 (1) and >50 (6). Figure 4.2 provides an illustration of the age distribution of the respondents

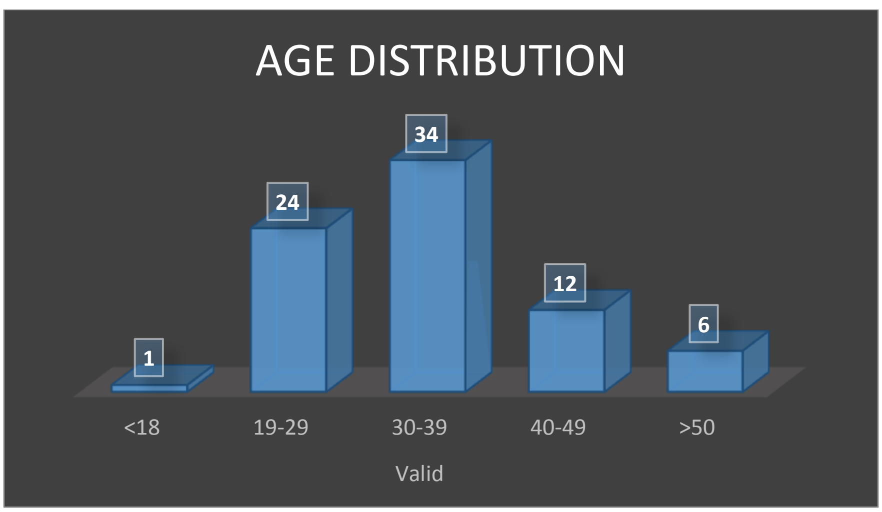

Figure 4.2: Age Distribution of the Research Participants Source: Research data 2019

Table 4.3 provides the highest education level of the research respondents that were involved in this study.

Table 4.3: Highest Education Level of the Respondents

Education Level

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Bachelor	47	61	61	61
	pHD	5	6.5	6.5	67.5
	Masters	10	13	13	80.5
	College Certificate	6	7.8	7.8	88.3
	Diploma	6	7.8	7.8	96.1
	High School	3	3.9	3.9	100.0
	Total	77	100.0	100.0	

From the table, it can be deduced that a majority of the respondents' highest level of education is a Bachelor degree certificate (47 respondents). 5 participants in the study had a PhD, 10 had a Master level education, there were 6 Diplomas and College certificates level participants respectively, and only 3 had a High School certificate as their highest level of education. Figure 4.3 provides a visual illustration of the information in the table above in the form of a bar graph.

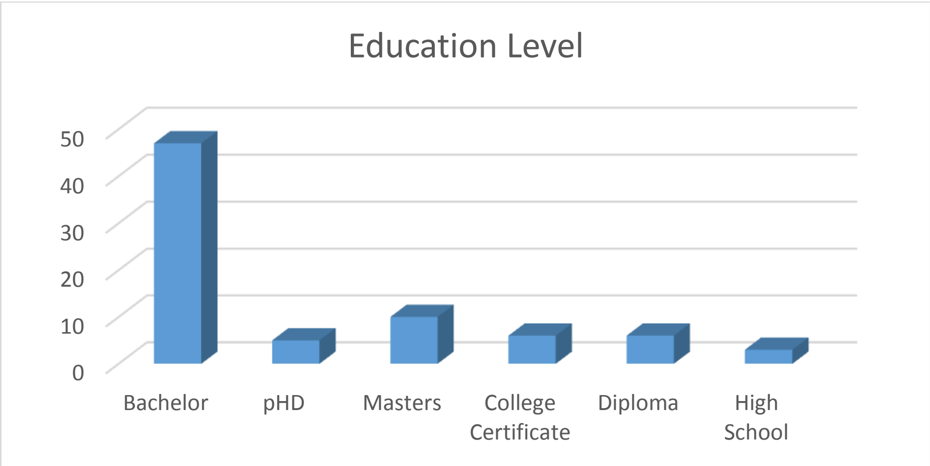

Figure 4.3: Education Level of the Respondents

The research was also keen on determining the frequency of usage of Zuku chatbots by the research respondents that were involved in this study. Table 4.4 below illustrates the frequency distribution of the research respondents.

Table 4.4: Frequency of Zuku Chatbots Usage by the Respondents

Experience

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	25	32.5	32.5	32.5
	2	33	42.9	42.9	75.3
	3	9	11.7	11.7	87.0
	4	9	11.7	11.7	98.7
	5	1	1.3	1.3	100.0
	Total	77	100.0	100.0	

From the table, it was deduced that out of the 77 respondents, 58 of the users stated that they had either never used a chatbot or rarely used it for communication purposes with Zuku staff members. It's only one user who stated that he frequently used chatbots to communicate with Zuku staff on issues pertaining to the services that they offered. The Figure 4.4 below presents a visual illustration of the information on frequency of usage of chatbots by the respondents.

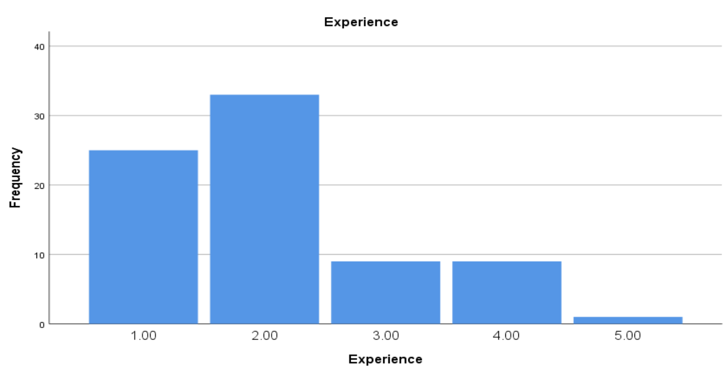

Figure 4.4: Frequency of Usage of Chatbots by the Respondents

4.4 Tests for Normality

To ensure that the responses from the questionnaires that had been filtered did not contain any missing data a descriptive analysis was conducted using SPSS on all the variables that were to be analysed to determine if there was missing data.

The next step was to conduct a multivariate normality analysis. A normality assessment was conducted to determine the type of distribution of the data collected. An important point to note is that, the term 'Normal' in statistics is used to describe a symmetrical, bell shaped curve whereby a majority of the frequency scores will be in the middle, while smaller frequencies are located in the extreme sections. To test for normality, the study is interested in determining the skewness and kurtosis values. Skewness is used to determine the symmetry of the distribution, whereby a positive skewness is an indicator that the distribution shifted towards the left, while a negative skewness shows that the distribution shifted towards the right. Based on the results after conducting descriptive analysis, the research found out that all the values had a negative skewness, meaning that the distribution had shifted towards the right. The maximum skewness value in this research was 1.790. It is important to point out that, in general, a skewness value of 1 indicates moderate skewness, and the value that was found falls within the range of 1, which can be concluded that the data collected had a moderate skewness. Kurtosis on the other hand provides information on the peakedness of the distribution. Kurtosis value of less than 1 are considered to be negligible, values from 1-10 indicate moderate non-normality, and values that are greater than 10 are an indication of severe non-normality. A positive kurtosis is an indicator of peaked distribution, while a negative one illustrates a flatter distribution. The maximum kurtosis value in this study was 5.049. The kurtosis value for a normal distribution is 3, and therefore, the dataset that was collected for this research can be described to have a normal distribution.

Table 4.5: Normality Tests Results

	Skewness		Kurtosis	
	Statistic	Std. Error	Statistic	Std. Error
Gender	-0.240	0.274	-1.995	0.541
Age	1.180	0.274	1.810	0.541
Experience	0.868	0.274	0.059	0.541
PF1	-0.240	0.274	-1.995	0.541
PF2	0.117	0.274	-1.125	0.541
PF3	0.014	0.274	-1.276	0.541
EE1	-0.425	0.274	-0.846	0.541
EE2	-0.790	0.274	-0.428	0.541
EE3	-0.661	0.274	-0.503	0.541
SF1	1.191	0.274	1.539	0.541
SF2	1.790	0.274	3.778	0.541
SF3	1.435	0.274	2.038	0.541
FC1	0.308	0.274	-0.801	0.541
FC2	0.318	0.274	-0.905	0.541
FC3	0.337	0.274	-0.904	0.541
S1	0.349	0.274	5.049	0.541
S2	0.341	0.274	0.512	0.541

4.5 Reliability Analysis

This is an important step before conducting factor analysis whereby, the study assesses the reliability of the scale used to confirm that it consistently reflects the variables that are being measured. To achieve this, the Cronbach Alpha is used to measure the scale of reliability. The Cronbach Alpha value varies from 0-1, and the higher variables are considered to be desirable. The Cronbach Alpha value was 0.773, which is a desirable value. This is illustrated in table 4.6 below.

Table 4.6: Cronbach Alpha Value

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.773	.769	14

4.6 Factor Analysis and identification of dominant factors

Factor analysis is a form of statistical analysis approach that allows a researcher to analyse the inter-relationships among the large number of variables that he is assessing, and to provide explanations of these variables in relation to their common factors. This statistical technique is ideal for investigating variable relationships of complex concepts such as determination of the adoption of chatbots in Kenya, whereby the study was forced to assess various underlying factors such as Performance Expectancy, Effort Expectancy, and Social Influence, which are difficult to measure. Therefore, the study had to formulate questions for these underlying factors, for instance, in the case of Performance analysis, three questions we developed, and used a Likert scale so that based on the responses of the research participants, the study could be able to measure these factors using Factor analysis in SPSS. For instance, in the performance expectancy questions, which has three questions, there will be a correlation on how respondent 1 responds to all the three questions whereby; if a research participant feels chatbots perform at a high level, then he will score highly on all the three questions. However, in questions that measure different traits such as performance and expectancy, they may not necessarily correlate as they will form their own complex matrix. In factor analysis, the study is trying to determine if the different correlations formed by different factors and come up with a unique adoption model based on the variables that are highly inter-correlated.

4.6.1 Kaiser Meyer Olkin (KMO) and Bartlett's Test of Sphericity

The KMO test is used to determine the suitability of the data collected for factor analysis. It assesses the sampling adequacy of individual variables in a model and the complete model. KMO values of between 0.5 and 1 are an indicator of sample adequacy. However, values that are lower than 0.6 are considered as not adequate for factor analysis. On the other hand, Bartlett test for sphericity is a test for null hypothesis in which a correlation matrix is considered to have an identity matrix. This means that it assesses if there is a redundancy between variables that can be summarized using some factors. The desirable or ideal Bartlett's value is $p<0.05$. The table below provides the results of the KMO and Bartlett tests.

Table 4.7: KMO and Bartlett Test for Sphericity

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.685
Bartlett's Test of Sphericity	Approx. Chi-Square	982.521
	Df	91
	Sig.	.000

The KMO and Bartlett test of sphrecity results are 0.685 and 0.000 respectively, which within the acceptable range to allow factor analysis to be conducted.

4.6.2 Factor Extraction

The next step in factor analysis is to conduct factor extraction whereby the principal component analysis (PCA) was determined to be the most appropriate extraction method for this study using the varimax rotation method. Table 4.8 provides the results of the factor extraction method that was applied in the research.

Table 4.8: Factor Extraction Method

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.021	28.720	28.720	4.021	28.720	28.720	2.800	19.998	19.998
2	2.966	21.184	49.905	2.966	21.184	49.905	2.792	19.944	39.942
3	2.664	19.031	68.936	2.664	19.031	68.936	2.791	19.939	59.881
4	1.574	11.244	80.180	1.574	11.244	80.180	2.486	17.755	77.636
5	1.215	8.681	88.861	1.215	8.681	88.861	1.572	11.226	88.861
6	.400	2.857	91.718						
7	.309	2.206	93.925						
8	.255	1.824	95.748						
9	.167	1.194	96.942						
10	.127	.907	97.850						
11	.116	.831	98.681						
12	.081	.581	99.262						
13	.071	.507	99.768						
14	.032	.232	100.000						

Extraction Method: Principal Component Analysis.

The PCA extraction method is used when the variables that are being analysed are highly associated, and the study intent is to reduce the number of observed variables to a small number of the principal components that will account for majority of the variance of the observed variables. The eigenvalues represent the variance, and using the SPSS, the PCA will only extract the factors that have an eigenvalue, which is greater than 1, and therefore in this study, 5 factors or components were displayed in the columns that are labelled *Extraction Sums of Squared Loadings*. The first five factors explain 88.861% of the variance.

Other than conducting eigenvalues analysis, a researcher can also conduct a scree plot inspection to assess the importance of each of the factors that he is analysing. Figure 4.5 is an illustration of the scree plot.

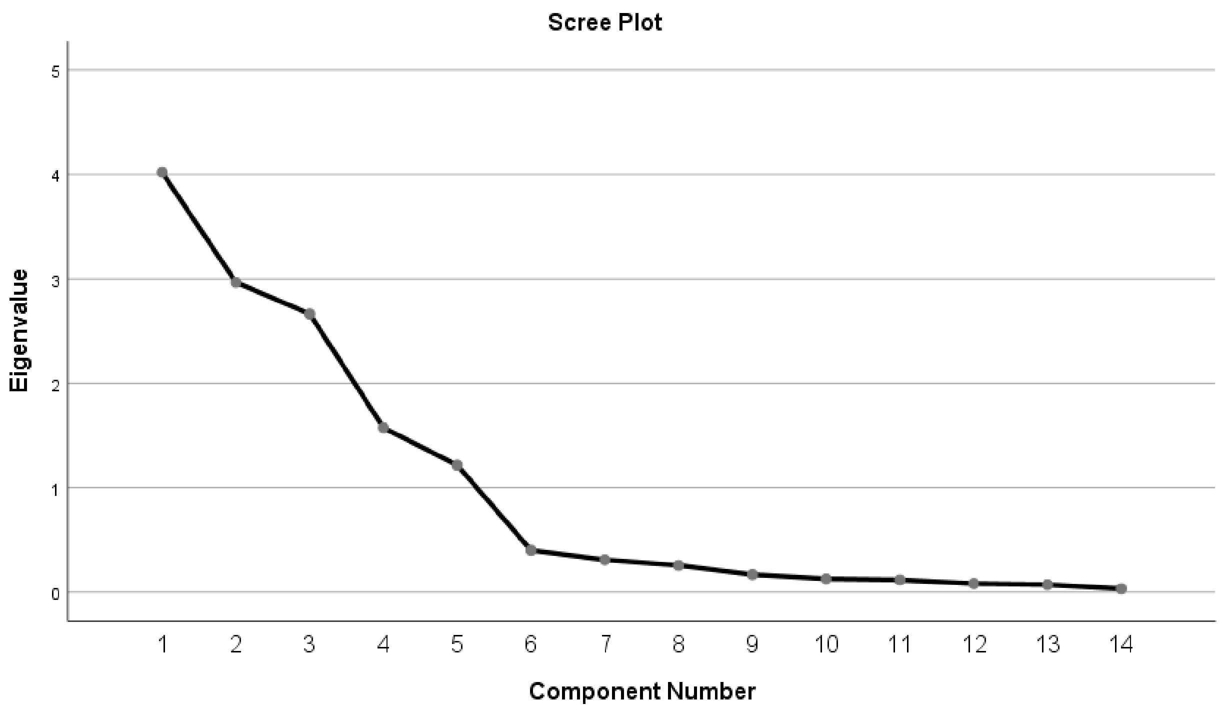

Figure 4.5: Scree Plot

The inflection point (change in the trend or direction) is at point 5, which confirms the eigenvalues of the study. In this plot what can be noted is after point 5, all the other plotted areas have a value of less than 1, and therefore they are discarded.

4.6.3 Factor Rotation

The five factors that were selected for further analysis using the rotated component matrix (the varimax rotation method) the results are provided in the table below.

Table 4.9: Varimax Rotation

Rotated Component Matrix[a]

	Component				
	1	2	3	4	5
EE2	.943	.102	.169	.132	.013
EE3	.930	.097	.188	.208	-.020
EE1	.902	.206	.241	.002	-.013
PF3	.149	.951	.020	-.071	-.005
PF1	.054	.949	-.090	.020	-.075
PF2	.160	.938	-.059	-.065	-.065
FC2	.136	-.026	.959	-.013	-.033
FC3	.217	-.077	.936	.006	.018
FC1	.196	-.031	.923	-.077	.022
SF2	.104	-.026	-.084	.907	.017
SF1	.094	-.072	-.020	.894	-.034
SF3	.086	-.008	.026	.881	-.125
S2	-.163	.041	.040	-.103	.886
S1	.153	-.169	-.036	-.023	.870

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

A loading of absolute value of more than 0.8 is acceptable. As can be seen in the rotated component matrix table, EE2, EE3 and EE1 load well in Component 1; PF3, PF1 and PF2 load in Component 2; FC2, FC3 and FC1 load in Component 3, SF2, SF1 and SF3 load in Component 4 and S2 and S1 load in Component 5.

4.6.4 Interpretation of the Factors

All the variables that were included in the conceptual framework: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Security Factors were supported by the results of factor analysis. Loadings that have an absolute value of more than 0.8 are accepted. All the factors had at-least one loading that had an absolute value of more than 0.8 as indicated in table 4.9: Varimax rotation.

4.7 Multiple Regression Analysis

Regression analysis is a statistical technique that is used to assess the relationship between dependent and independent variables in the study. The study applied the multiple linear regression analysis to determine the relationship between chatbot utilization (dependent variable) and the five independent variables that were used in this study. The multiple regression analysis was applied in this study to test the research hypothesis, and the regression model was presented as follows:

$$CU = a + c_1PE + c_2EE + c_3SI + c_4FC + c_5S + e$$

Whereby

CU= Chat-bot Utilization

PE= Performance Expectancy

EE= Effort Expectancy

SI= Social Influence

FC=Facilitating Conditions

S= Security

a= Constant where regression intercepts the y axis

c= Regression co-efficients

e= Random error

4.7.1 Assumptions for Regression Analysis and Analysis of Variance (ANOVA)

The following assumptions were tested to determine the properness of the analysis.

1. Absence of outliers: It is important to point out that for an outlier whose standardized value is greater than 3.3 should be dropped from all the regression models. In this study, the data file with the greatest standardized residual was -3.15068.

2. Linearity: To identify non-linear patterns, examination of the residual scatter was used, and the scatter plot revealed that the data that the study collected had a linear relationship.
3. Tolerance and Multicollinearity: Tolerance= $1-R^2$ where R^2 is the multiple of R of a given dependent variable regressed on the independent variables. If the tolerance value is less than 0.20, the independent variable should be excluded from analysis due to its multi-collinearity.
4. Variance Inflation Factor (VIF): It is the reciprocal of tolerance.

To test for and identify multi-collinearity (when two variables are highly correlated) in the independent variables that we are assessing in this study, the first test was undertaking the Bivariate correlation test. The values from this test are shown in table 10 below:

Table 4.10: Variables Correlations

Correlations

		PF1	PF2	PF3	EE1	EE2	EE3	SF1	SF2	SF3	FC1	FC2	FC3	S1	S2
PF1	Pearson Correlation	1	.869**	.874**	.208	.137	.141	-.029	.000	.003	-.103	-.088	-.152	-.183	-.071
	Sig. (2-tailed)		.000	.000	.070	.236	.220	.802	.999	.977	.374	.445	.186	.111	.538
PF2	Pearson Correlation	.869**	1	.887**	.294**	.224	.234*	-.123	-.052	-.040	-.057	-.060	-.074	-.170	-.056
	Sig. (2-tailed)	.000		.000	.009	.051	.040	.285	.656	.729	.622	.607	.524	.140	.626
PF3	Pearson Correlation	.874**	.887**	1	.356**	.229*	.196	-.105	-.085	-.051	.026	.011	-.028	-.134	.007
	Sig. (2-tailed)	.000	.000		.001	.045	.088	.365	.462	.660	.822	.922	.810	.246	.951
EE1	Pearson Correlation	.208	.294**	.356**	1	.879**	.878**	.082	.066	.092	.411**	.326**	.392**	.028	-.089
	Sig. (2-tailed)	.070	.009	.001		.000	.000	.476	.568	.426	.000	.004	.000	.807	.441
EE2	Pearson Correlation	.137	.224	.229*	.879**	1	.929**	.174	.207	.212	.325**	.288*	.355**	.112	-.128
	Sig. (2-tailed)	.236	.051	.045	.000		.000	.129	.071	.064	.004	.011	.002	.332	.267
EE3	Pearson Correlation	.141	.234*	.196	.878**	.929**	1	.267*	.264*	.257*	.318**	.321**	.373**	.095	-.174
	Sig. (2-tailed)	.220	.040	.088	.000	.000		.019	.020	.024	.005	.004	.001	.412	.131

SF1	Pearson Correlation	-.029	-.123	-.105	.082	.174	.267*	1	.746**	.694**	-.051	-.019	.000	-.021	-.149
	Sig. (2-tailed)	.802	.285	.365	.476	.129	.019		.000	.000	.659	.868	1.000	.856	.195
SF2	Pearson Correlation	.000	-.052	-.085	.066	.207	.264*	.746**	1	.718**	-.121	-.082	-.034	-.009	-.092
	Sig. (2-tailed)	.999	.656	.462	.568	.071	.020	.000		.000	.293	.479	.772	.935	.427
SF3	Pearson Correlation	.003	-.040	-.051	.092	.212	.257*	.694**	.718**	1	-.037	.028	.038	-.103	-.203
	Sig. (2-tailed)	.977	.729	.660	.426	.064	.024	.000	.000		.749	.812	.745	.374	.077
FC1	Pearson Correlation	-.103	-.057	.026	.411**	.325**	.318**	-.051	-.121	-.037	1	.864**	.855**	.017	.032
	Sig. (2-tailed)	.374	.622	.822	.000	.004	.005	.659	.293	.749		.000	.000	.885	.781
FC2	Pearson Correlation	-.088	-.060	.011	.326**	.288*	.321**	-.019	-.082	.028	.864**	1	.918**	-.018	-.029
	Sig. (2-tailed)	.445	.607	.922	.004	.011	.004	.868	.479	.812	.000		.000	.877	.802
FC3	Pearson Correlation	-.152	-.074	-.028	.392**	.355**	.373**	.000	-.034	.038	.855**	.918**	1	.048	-.006
	Sig. (2-tailed)	.186	.524	.810	.000	.002	.001	1.000	.772	.745	.000	.000		.678	.956
S1	Pearson Correlation	-.183	-.170	-.134	.028	.112	.095	-.021	-.009	-.103	.017	-.018	.048	1	.560**
	Sig. (2-tailed)	.111	.140	.246	.807	.332	.412	.856	.935	.374	.885	.877	.678		.000
S2	Pearson Correlation	-.071	-.056	.007	-.089	-.128	-.174	-.149	-.092	-.203	.032	-.029	-.006	.560**	1
	Sig. (2-tailed)	.538	.626	.951	.441	.267	.131	.195	.427	.077	.781	.802	.956	.000	
	N	77	77	77	77	77	77	77	77	77	77	77	77	77	77

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

*. Correlation is significant at the 0.05 level (2-tailed).

As there is no agreed value to determine the collinearity between different variables after conducting a bi-variate correlation test, the study selected the value of 0.80 as a cut-off point. This means that any value that is higher than 0.80 is an indicator of high correlation between variables. The values marked in red show the high correlation between the variables involved, for instance, in PF1 and PF2. To verify the multi-collinearity of the variables that were used in this study a second test was conducted, which is the linear regression analysis with a particular interest of conducting collinearity diagnostics. After running the test, the result that the study is interested in is the Coefficients table that contains the collinearity statistics of Tolerance and VIF. The values are as indicated in table 4.11 below:

Table 4.11: Coefficients Table Results 1

Coefficients[a]

Model		Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	PF1	.165	**6.068**
	PF2	.130	**7.712**
	PF3	.109	**9.190**
	EE1	.103	**9.680**
	EE2	.110	**9.116**
	EE3	.068	**14.789**
	SF1	.343	2.918
	SF2	.330	3.027
	SF3	.402	2.487
	FC1	.190	**5.262**
	FC2	.105	**9.556**
	FC3	.120	**8.359**
	S1	.543	1.842
	S2	.570	1.755

a. Dependent Variable: C.U.

VIF values that are greater than 4 indicate multi-collinearity problems, while those below 1.0 indicate that multi-collinearity is not a problem. There were a couple of independent variables, which had a higher value that 4, and they have been marked in bold. Therefore, the best approach to eliminate the multi-collinearity issues will be to eliminate some of the problematic variables such as PF2 and PF3; EE2 and EE3; and FC2 and FC3, and then conduct the linear regression analysis again. The results have been presented in table 12 below:

Table 4.12: Coefficients Table Results 2

Coefficients[a]

Model		Collinearity Statistics Tolerance	VIF
1	PF1	.869	1.151
	EE1	.729	1.372
	SF1	.387	2.586
	SF2	.354	2.826
	SF3	.413	2.422
	FC1	.760	1.315
	S1	.644	1.552
	S2	.642	1.557

a. Dependent Variable: C.U.

Looking at the VIF values, one can see that there is none with a value of greater than 4, which is an indicator that there are no multi-collinearity problems.

4.8 Hypothesis Testing

4.8.1 Test Results for Direct Effects

The study was evaluating five independent variables in the regression analysis against chatbot utilization. Table 4.13 provides an illustration of the results for testing for direct effects.

Table 4.13: Testing for Direct Effects

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	T	Sig.
1	(Constant)	2.222	.873		2.545	.013
	PF1	.019	.064	.036	.293	.770
	EE1	.103	.072	.190	1.423	.159
	SF1	.067	.134	.092	.501	.618
	SF2	.008	.131	.012	.065	.948
	SF3	.065	.129	.090	.506	.615
	FC1	.058	.067	.114	.871	.387
	S1	-.021	.227	-.013	-.094	.925
	S2	.217	.165	.187	1.316	.192

a. Dependent Variable: C.U.

The results of this study indicate that with the exception of the S1 independent variable, the other variables have a positive effect on chatbot utilization for Zuku customers in Kenya. EE1 has the most influential impact on chatbot utilization, followed by S2 and FC1.

4.8.2 Testing for Moderating Effects

To determine the moderating effects, the beta weight and multiple R-square values are used. It is important to point out that the Beta values should not be less than 0.1. However, if they are beyond 1, then it is a sign of multi-collinearity. The following is the scale that is used:

- If the Beta value of between 0.1 and 0.2 then this is a small effect
- Values of between 0.3 and 0.5 are an indicator of medium effect
- Above 0.50 shows large effect
- Less than 0.1 points out that it has no effect on the variable

Table 4.14 is a presentation of the moderating effects.

Table 4.14: Moderating Effects

	R^2	Beta	Significance
PF+A+E	0.015	0.123	0.285
EE+A+G+E	0.080	0.284	0.012
A+G+SF1	0.013	-0.113	0.328
A+G+SF2	0.006	-0.078	0.498
A+G+SF3	0.000	-0.014	0.903
A+G+FC1	0.030	0.175	0.129
S1+A+G+E	0.017	0.129	0.264
S2+A+G+E	0.009	0.395	0.411

The results presented in table 4.14 show how different moderating factors such as age, experience and gender affect the dependent variables that were selected in this study. Age and experience have a small effect on performance expectancy as has been indicated by the beta value of 0.123. Age, experience, and gender have a medium effect on effort expectancy based on their beta value of 0.284. Age and gender have no effect on social factor based on the beta values of -0.113, -0.078 and -0.014. Also, age and gender have a small effect on facilitating conditions, based on its beta value of 0.175. In addition to that age, gender and experience have a large effect on security based on the beta values of 0.129 and 0.395.

4.9 The Resulting Model

The model that has been illustrated in this section based on multiple regression shows that all the five independent factors have a positive relationship with chatbot utilization in the adoption of chatbots in Kenya. The variables were determined as follows:

1. Performance expectancy is slightly moderated by age and experience

2. Effort expectancy is moderately moderated by age, gender, and experience
3. In social expectancy, it is not moderated by age and gender
4. In facilitating conditions, it is slightly moderated by age and experience
5. Security is largely moderated by age, gender and experience

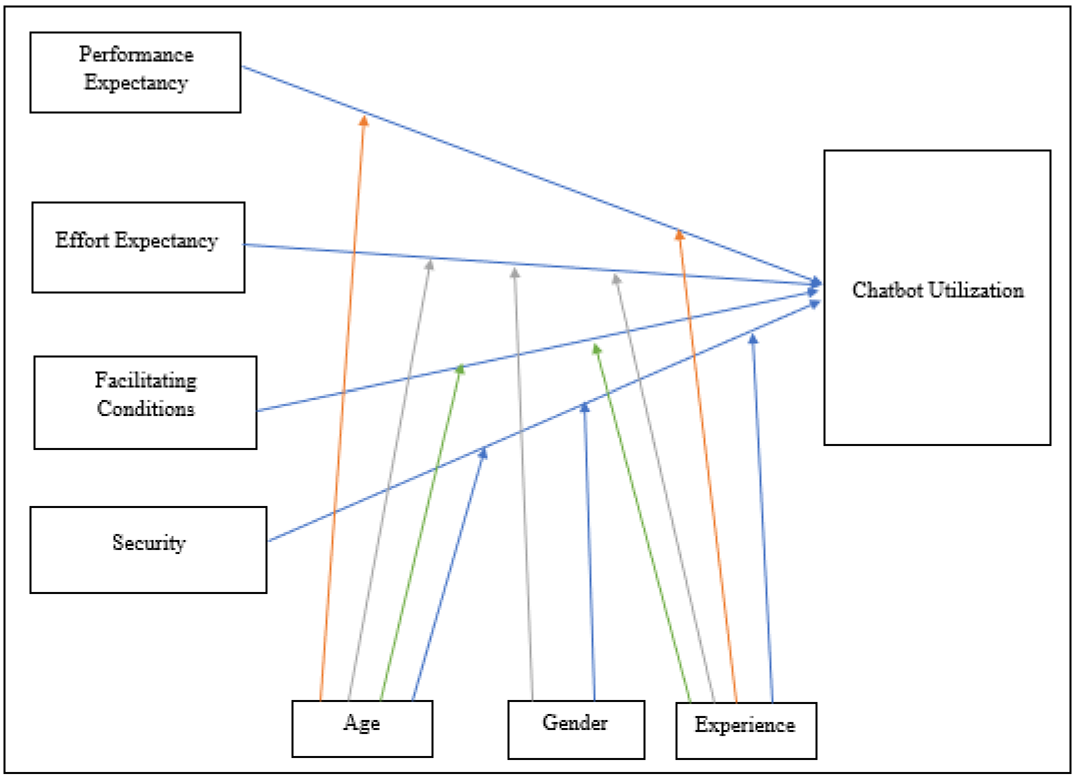

Figure 4.6: Resulting Model

There were slight variations between the resulting model, which the study developed from the results of the study, and the conceptual framework, which was created from the existing gaps of the theories that the study used. However, before providing an explanation of the differences between the conceptual framework and the resulting model, it is important to mention the similarities of these models. In both of these models, the factors that affect chatbot utilization are performance expectancy, effort expectancy, facilitating conditions, and security. Also, the levels that these factors affect users chatbot utilization capability is affected by the following moderating factors age, gender and experience.

In the conceptual framework, performance expectancy is only affected by age, while in the resulting model, it is affected by age and gender. According to Venkatesh et al. (2003), performance expectancy is the degree of ease a user expects when he or she is using a system for a specific purpose. Kijsanayotin et al. (2009) added the performance expectancy is an important predictor for the adoption of new technology. Venkatesh et al. (2003) integrated various concepts from different models in the construction of performance expectancy-perceived usefulness, extrinsic motivation, relative advantage and outcome expectations. Perceived usefulness refers to an individual's perception of the likelihood that the use of a specific, or in this case a new system will enhance its intended performance. Extrinsic motivation refers to an activity that will bring about external outcomes such as rewards. Relative advantage refers to a product's degree of superiority and attractiveness in comparison to other similar products assessed using value in comparison to its overall cost, and outcome expectations can be defined as is the effect of an action.

The disparity of the two models from the performance expectancy perspective is that, there is a high likelihood that a majority of the users of this chatbot from Zuku are young adults (20-35 years). This group of individuals are highly innovative and less resistant to the adoption of new technology. In addition to that, they are less likely to experience usability issues than is the case for the older users. In addition to that, they are highly likely to have been influenced by perceived usefulness, extrinsic motivation, relative advantage and outcome expectations of chatbots. It explains why in the resulting model performance expectancy was affected by age and experience.

Contrary to the previous studies, in this study, the results indicated that Zuku consumers did not feel that social influence had an effect on them when it comes to chatbot utilization. Kulviwat, Bruner and Al-Shuridah (2009) noted that the impact of social influence on consumers' adoption intention is mainly affected by their attitude. In addition to that, these researchers were able to establish that the relationship between social influence and adoption intention is stronger when the innovation is being publicly consumed, rather than when it is privately consumed. This argument can be used to explain why chatbot utilization by Zuku consumers was not affected by social influence as it is a privately consumed innovation. According to a news article by Business Daily in 2018, it was estimated that the number of Zuku subscribed customers was 112,155(Njanja, 2018). These individuals are mainly in the urban areas, and the product is used mainly for entertainment purposes constituting it as a privately consumed innovation at the moment.

Effort expectancy and security were affected by age, gender and experience. In addition to that, these were the only factors in both the conceptual framework and resulting model that were influenced by gender. The reason for this is that, firstly, all users during their adoption of a new technology want it to be less complex, while fulfilling their needs. If they struggle to use, then it will be difficult for them to adopt the new technology. Secondly, all users need to be assured that the use of a new technology will not compromise the security of their data in a system. The two explanations can be used to explain why all the moderating factors affected both the effort expectancy and security.

CHAPTER FIVE: CONCLUSIONS AND RECOMMEDATIONS

5.1 Introduction

In this project, the study presented and discussed the findings that focused on formulating a model that can be used to explain the adoption patterns or trends of chatbots in Kenya with a particular focus on Zuku subscribers. A conceptual model developed was tested using the data collected from the research participants and a resulting model was drawn in chapter four based on the study results.

5.2 Research Conclusions

In this section, the study makes a presentation of how the current research objectives were achieved. Based on the study results, the study established that performance expectancy, effort expectancy, facilitating conditions and security were the main determinants for adoption of chatbots in Kenya. In an organizational setting, the management of Zuku needs to increase or improve the performance expectancy, effort expectancy, facilitating conditions and security measures to encourage increased usage among its customers.

The study results further established that age, gender and experience were moderating factors on the constructs that were used in this study. Age had an impact on all the four factors (performance expectancy, effort expectancy, facilitating conditions and security). Age and experience were moderating factors on performance expectancy and facilitating conditions. Age, gender and experience were moderating factors on effort expectancy and security. The study deduced that when age and gender were used as moderating factors, they had no impact on social factors construct.

5.3 Research Limitations

The study encountered various challenges when conducting this research. The first challenge was to convince research participants, especially the elderly (50+ years) to participate in this study. A majority of them were either reluctant or suspicious of the study intentions in this study and this led to less elderly women participating in this study. The second challenge experienced is the small-time frame in terms of usage of the chatbot by Zuku clients, mainly one or two years, their expectations and perceptions were a little bit biased because they did still did not have a good understanding of how to effect use this technological tool to enhance their communication with Zuku.

5.4 Contributions to Knowledge

The research has increased the knowledge level in the adoption of chatbots in Kenya. The study adopted the key drivers that will likely influence an increase in the number of participants who will willingly use these devices to interact with tech-savvy companies such as Zuku (that have begun integrating chatbots as part of their customer services). The information in this research acts as a guide to companies that want to adopt this technology in terms of the factors that they should mainly focus on to influence high adoption rates for their targeted audience. It can also be used by future researchers as a base in terms of developing more effective technology adoption models in the country

5.5 Recommendations for Future Studies

Chatbot utilization is relative a new concept of in Kenya and its adoption by organizations have many benefits attributed to it. Future studies should focus on assessing why social factors are not instrumental in terms of affecting adoption of chatbots as a new technology in Kenya.

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APPENDIX 2: QUESTIONNAIRE

I am a student at the University of Nairobi and am conducting an academic research study aimed at developing a framework for chatbots adoption in Kenya among service providers such as Zuku. I identified you as one of the ZUKU customers through a listing exercise that was done in selected estates around Nairobi. Kindly assist with the information required in this questionnaire as accurately as possible. All the information you provide will be kept confidential and will only be used for the purpose of my academic research study.

A. PERSONAL DETAILS

Gender:

[_] Male [_] Female

Age:

[_] Less than 18 years [_] 19-29 years [_] 30-39 years [_] 40-49 years [_] >50

Highest education level

[_] High School Certificate [_] Certificate College [_] Diploma [_] Bachelor [_] Others (State)

How often do you utilize Zuku Telegram chatbots to interact with your service provider Zuku?

[_] Never [_] Occasionally [_] Sometimes [_] Often [_] Always

How long have you been using the chat-bot to interact with your service provider Zuku?

[_] Less than one month [_] Less than three months [_] Between three and six months

[_] One year [_] More than one year

B. PERFORMANCE EXPECTANCY

1. Chatbots are effective in terms of interacting with potential customers and sharing important company information that they need

[_] Strongly Disagree [_] Disagree [_] Neutral [_] Agree [_] Strongly Agree

2. Chatbots facilitate better company-client interaction because of their instant replies to customer queries

[_] Strongly Disagree [_] Disagree [_] Neutral [_] Agree [_] Strongly Agree

3. The chatbots that I have interacted are inter-operable meaning that they support multi-channels such as desktop and mobile applications/messengers

[_] Strongly Disagree [_] Disagree [_] Neutral [_] Agree [_] Strongly Agree

C. EFFORT EXPECTANCY

1. I find it very easy to interact with the company through the use of chatbots

[_] Strongly Disagree [_] Disagree [_] Neutral [_] Agree [_] Strongly Agree

2. I find it relatively easy to use the chatbot

[_] Strongly Disagree [_] Disagree [_] Neutral [_] Agree [_] Strongly Agree

3. Learning to interact/operate the chatbots was relatively easy

[_] Strongly Disagree [_] Disagree [_] Neutral [_] Agree [_] Strongly Agree

D. SOCIAL FACTORS

1. People who influence my behavior/choices have advised me to use chatbots as my main mode of communication with companies

[_] Strongly Disagree [_] Disagree [_] Neutral [_] Agree [_] Strongly Agree

2. It is an emerging trend to use chatbots among my peers to seek assistance on company information, and other services rather than human support staff

[_] Strongly Disagree [_] Disagree [_] Neutral [_] Agree [_] Strongly Agree

E. FACILITATING CONDITIONS

1. Chatbots have predefined processes that enhance my experience when interacting with them such as providing me with additional information that relate to my queries

[_] Strongly Disagree [_] Disagree [_] Neutral [_] Agree [_] Strongly Agree

2. Zuku officials can easily be contacted to offer assistance on how to navigate or use the chatbot whenever one is stuck or faces challenges using this technology?

[_] Strongly Disagree [_] Disagree [_] Neutral [_] Agree [_] Strongly Agree

3. Zuku chatbot is easy to use for an average tech-savvy client?

[_] Strongly Disagree [_] Disagree [_] Neutral [_] Agree [_] Strongly Agree

F. SECURITY

1. Do you feel that the chatbots have been secured enough to enhance your utilization of the device?

[_] Strongly Disagree [_] Disagree [_] Neutral [_] Agree [_] Strongly Agree

2. Do you agree that the data information that you feed into a chatbot is stored securely and therefore there is no likelihood that it can be accessed by unauthorized third parties?

[_] Strongly Disagree [_] Disagree [_] Neutral [_] Agree [_] Strongly Agree

APPENDIX 3: PROJECT PLAN

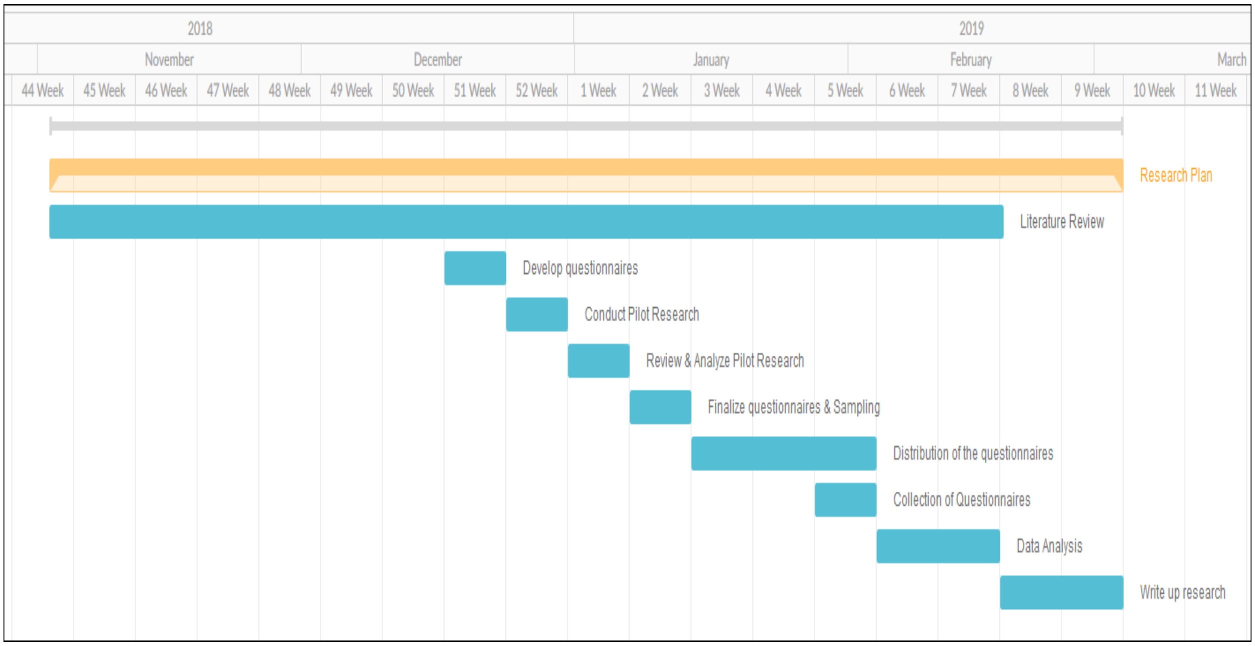
Budget Plan

Activity	Cost	Justification
Equipment	90,000.00	Laptop & Software for data analysis
Airtime	1,000.00	Contacting research participants
Internet	5,000.00	Distribution of questionnaires & conducting research
Printing	1,000.00	Reports for submission
Total	97,000.00	

Research plan

	Task	Earliest start date	Duration (weeks)	Parallel or sequential	Dependent
A	Literature Review	1-Nov-18	23	Parallel	-
B	Develop questionnaires	17-Dec-18	1	Sequential	-
C	Conduct Pilot Research	24-Dec-18	2	Sequential	B
D	Review & Analyze Pilot Research	31-Dec-18	1	Sequential	C
E	Finalize questionnaires & Sampling	7-Jan-19	1	Sequential	D
F	Distribution of the questionnaires	14-Jan-19	4	Sequential	E
H	Collection of Questionnaires	4-Feb-19	1	Sequential	F
I	Data Analysis	11-Feb-19	2	Sequential	H
J	Write up research	18-Feb-18	2	Parallel	A,I

Gantt Chat:


2018
2019
November
December
January
February
March
44 Week
45 Week
46 Week
47 Week
48 Week
49 Week
50 Week
51 Week
52 Week
1 Week
2 Week
3 Week
4 Week
5 Week
6 Week
7 Week
8 Week
9 Week
10 Week
11 Week
Research Plan
Literature Review
Develop questionnaires
Conduct Pilot Research
Review & Analyze Pilot Research
Finalize questionnaires & Sampling
Distribution of the questionnaires
Collection of Questionnaires
Data Analysis
Write up research