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Artificial Intelligence Chatbot Adoption Framework for Real-Time Customer Care Support in Kenya

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ABSTRACT

In today's society, most if not all sectors digitize and automate in order to become more efficient. The increasing availability and sophistication of software technologies disrupt labor markets by making workers redundant. Within this context, a significant change is companies' introduction of chatbots as a supplement to human customer support is vital. Chatbots are computer programs that interact with humans through natural language. The purpose of chatbots is to simulate a human conversation in response to natural language input through text or voice. There seems to be no proper guidelines for adoption of chatbots for provision of customer care support services in telecommunication industry in Kenya. The aim of this research was to develop a framework for adoption of artificially intelligent chatbot application in telecommunication industry. This was achieved through determination of the status of implementation of chatbots in Kenya and identification of key metrics that served as indicators for chatbot adoption. The metrics were identified through review of previous technology adoption frameworks and models. The study adopted mixed methods where qualitative and quantitative data was collected using interview schedules and questionnaires respectively. Content analysis was used in analyzing qualitative data. Quantitative data was analyzed descriptively and results were presented using tables. The target population included experts in the field of AI in two telecommunication firms in Kenya. The study sample was drawn, using Delphi technique, from the two telecommunication firms. The descriptive and principal component analysis were utilized. The results of this research study will be crucial to all telecommunication firms in guiding them on the most effective and efficient way of adopting AI chatbot application for customer support services.

Keywords : Artificial Intelligence, Chatbot, Customer Experience.

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I. INTRODUCTION

Technology has changed how people, organizations and firms function nowadays. This development will have extensive global impact on performance, resilience and competitiveness for industries. The technologies in future at the convergence of intelligent machines, data and people will create opportunities for improvement based on new business models, transformed behavior and well-informed decision making. These intelligent technologies including, artificial intelligence (AI), virtual reality (VR), augmented reality (AR), text mining, Internet of Things (IoT), lead to enhanced predictive capabilities, improved experiences, and real time actionable insights. Whether we look at Business-to-Consumer (B2C) or Business-to-Business (B2B) settings, big data, information technology, artificial intelligence, business intelligence & analytics, new technology delivery platforms are emerging [1][2] [3][4].

In addition, there is increase in the use of service technologies which has led to increased research attention due to problems in service marketing. These research attentions are being done in disciplines such as information systems and computer science [5][6][7]. This shows the need for multidisciplinary service research [8] while preserving a vigorous service-theoretic focus. This is specially the case in service analytics [9], an area ranging from Business-to-Consumer Customer Relationship Management metrics, to advanced Business-to-Business IoT metrics and information technology infrastructure, both hardware and software supporting collection, measurement and reporting of cloud-based software infrastructure [10]. Service analytics are emerging with the rise in artificially intelligent agents such as IBM Watson [12]. Customer experience in the modern service context is concerned primarily with measurement and integration of customer interactions with organization or brand [11]. This encompasses new trends ranging from chatbots [13], powered by advanced AI applications to deliver on-demand and refined customer service and monitoring feedback from customers in real-time [8]. Furthermore, customers are now performing their everyday activities with the support of technology [14]. This includes; augmented reality systems in retailing, healthcare and education which enable users to understand their environment in a completely new way. These trends sequentially translate into new suggestions for both customers and managers. The rapid advancements in technology in today's services demand relooking at science frameworks that are in existence, into lenses by which academia can assist managers detect and find solutions to real-world problems in real time while maintaining customer-centricity.

However, researchers can assist customers self-detect and find solutions to problems which will benefit customers everyday lives. For scientists, these developments need questions to be asked on, how to use new technology to develop business value, measure and improve customer experience [15][16] and for questions to be re asked, for instance, technology readiness [17], engagement and big data [4], quantifying e-service quality [18]. When data or information is not managed properly, it results in negative customer experience which leads to low customer satisfaction. This deficiency takes place in several situations because customer experience (CX) is entire compendium of touch-points during an interaction between the customer and a brand, firm or business [19], which spans from advertising, customer care, trustworthiness and service or product features [20].

Therefore, it is important for industries to structure customer experience (CX) across these various interactions with customers. Nonetheless, many industries fail to consider their services and products as an all-round experience, some firms focus on social media and websites, others concentrate on face-to-face or physical retail services or on-the-phone customer service interaction [21]. Allen [22], did a research study to find out if both customers and businesses perceive same CX quality. It was discovered that even-though 80% of firms considered they offered a great CX, only eight percent of their clients expressed they got satisfied by experience they received. The study recognized discrepancy in the way customers and firms perceived the quality of CX. Customer satisfaction and perceived quality of service are two demonstrated success metrics for customer service providers [23] [24]. However, how can we measure customer satisfaction?

Kim [25] identified, value added services to enhance convenience and enjoyment, and customer support, to quickly process customer requests. These are two critical metrics for customer satisfaction. Customers making a phone call to firms for customer care service support results in low satisfaction, not mentioning long waits before talking to available human agents [26][27]. GetHuman.com was created in 2007 to provide shortcuts for customers to reduce long waits while calling customer care support numbers in big firms. Time Warner Cable Spectrum (TWCS) had a bad reputation in customer service support. They decided to use online chat support that was available 24 seven to address poor customer service issues. The effort and time customers require to find solutions to their problems and access to information is a factor to be considered in successful CX.

There is proliferation of technologies and there are many emerging technologies. The demand for prompt and frequent feedback and support for customers in various organizations gives a competitive advantage to the organization. The alternative to human customer care support is embracing the Artificial intelligence systems such as Chatbot applications. Despite the fact that there is some limited level of adoption of chatbot in some organizations such as telecommunications, the adoption process itself is haphazard. Therefore, there is need for a well formulated guide to support full adoption of chatbots. This paper presents artificial intelligence chatbot adoption framework for real-time customer care support which serves as a guide for adoption of AI chatbot application in telecommunication industry.

II. Basic concepts of artificial intelligence

Computers and data science have been deployed to image recognition, process natural language, learn and draw from past experience. The use of the techniques of computer science to perform these tasks is collectively known as Artificial Intelligence (AI). The application of AI today abounds: diagnostics in healthcare, translation of languages, self-driving cars, and in financial services for risk profiling and portfolio management. Machine learning is characterized by the little or lack of human intervention with the enablement of algorithms [28].

2.1 Machine Learning

Machine learning is a basic concept of artificial intelligence since the field begun [29]. It is the application of AI which provides applications with ability to learn and become better via computer algorithms [30] [31]. There are three types of machine learning algorithms: Unsupervised learning is defined as the ability of machines to get patterns in an input stream without the need for labelling the inputs by a human. Supervised learning consists of numerical regression and classification. The human is required to label input data. Classification determines which category something belongs in, which occurs after an algorithm analyzes various examples of things (data) from several different categories. Regression results in a function which describes causal relationships between input and output, and predict how the output data ought to change as input data changes [31].

Both regression and classifier learners are observed as function approximators, striving to learn unknown functions. For instance, spam classifier is regarded as a function which learns and maps texts of an email to either spam or not spam. The theory of computational learning assesses learners via computational complexity by sample complexity or other concepts of optimization [32]. With reinforcement learning [33], the agents are rewarded for good responses and penalized for bad responses. The agents use the sequence of reward and penalties to form strategies to operate in their problem space. With machine learning algorithms, AI chatbot application can learn from past interaction with customers and customize responses to specific individuals and services through prediction.

2.2 Natural Language Processing (NLP)

NLP [34], provides machines with ability to read and comprehend human natural language. A sufficient and powerful NLP application would facilitate natural language user interfaces and acquirement of knowledge from written sources, for example, Newswire text. Applications of NLP include, mining of texts, answering questions, information retrieval [35], and machine translation [36]. Many present approaches use frequencies of occurrences of words to construct syntactical representation of text. Some searching strategies like keyword spotting are common and scalable but are not effective, for example, if one has a query to search for a, "dog", the search may only match documents having the word "dog" but may miss out on the word, "poodle". Lexical affinity uses word occurrence like, "accident" to evaluate the sentiments of documents.

Modern statistical Natural Language Processing approaches combine all these techniques and often attain a paragraph or page level accuracy, but they do not have semantic understanding needed to categorize isolated sentences in the right way. A part from problems in encoding semantic common-sense knowledge, the available semantic Natural Language Processing scales imperfectly to be practical in business enterprise applications. Above semantic NLP, the main aim of NLP is to consolidate an understanding of common-sense reasoning [37]. The chatbot application adopted should read and understand English language. As an example, if a human says he or she has a running nose and smelling feet, the chatbot application should understand just like human. The chatbot application should not escalate conversation by saying, “The feet should run and the nose, smell.” Therefore, NLP can be used for recognition.

2.3 Natural Language Understanding (NLU)

NLU is a part of NLP in AI that deals with the ability to read text, process it and understand the meaning. Natural Language Understanding is regarded as AI-hard problem [38]. NLU involves disassembling of the input, then parsing the input into data that can be analyzed by the analysts or machine learning experts. This part is more complex than the reverse process of converting data to language because of the unexpected occurrences of symbols or words or phrases or unexpected features in any input. Human beings have a tendency to use abbreviations, or some slang word that might not even be in the language. The Natural Language Understanding algorithm should be able to tackle such difficulties and carry out the conversion smoothly [38].

2.4 Human Computer Interaction (HCI)

HCI deals with the interactions and relationships between computers and humans. HCI is more than user interfaces and “screen-deep'' [39]. Human Computer interaction is a field covering different areas [40]. In the early years of the history of HCI, the focus was on user interfaces, especially GUIs, using windows, menus, icons, mice, to develop usable applications. As user interface problems could be understood, the main HCI concerns shifted from interface to address observations as expressed by D. Engelbart, who said that, "If the ease of use was the only permitted criteria, people would have stuck to tricycles, and not try bicycles." Present HCI research goals [41] deals with shared understanding, tasks, justifications, explanations, and not just interfaces.

The new key challenges improve how people utilize computers to think, work, communicate, critique, learn, argue, explain, debate, decide, observe, calculate, design and simulate. The chatbot application should have a simple interface.

2.5 Natural Language Processing as part of Human Computer Interaction

Developing a system that can both understand natural language and respond appropriately is not enough if we pursue true HCI. The system will also need a strategy as to how it can sustain a fluid conversation. It could harm the flow of the conversation, for instance, if the responses would interrupt the collocutor or if he or she has to wait too long for the responses. Another vital part of the dialog strategy is the acknowledgement of the collocutor and the uttered sentences by giving an appropriate back-channel feedback. According to the paper of Cantrell [42], the lack of this feedback can cause a human collocutor to become unsure of whether or not he or she is being understood. To enable a dialog strategy to function properly, it should be implemented in an early stage. There, it must analyze the flow of the utterances to detect any characteristic behavior.

Cantrell [42] suggest to focus on non-speech noise, for instant pauses. They note that the timing of the feedback is not even that important and can occur between immediately after the utterance to a few seconds later. In addition, Cole [43] propose including other nonspeech noises as well, for example, filled pauses, laughter, inhalation and coughing. A more robust approach can be attained by using the prosody of one, his or her voice to determine the proper strategy [42]. To this end, the system must analyze the rate, pitch and amplitude of the voice. In addition to detecting the characteristic behavior of a non-speech moment, this could be put in use for responding appropriately to a certain emotion like a robotic companion for the elderly or chatbot application for customer care.

2.6 Chatbot Technologies and Implementation.

Chatbot applications are computer applications which interact with people via natural language [44]. The main reason for humans to use chatbots is productivity, meaning quicker answer with less effort. Moreover, chatbots have been implemented with a variety of reasons, such as provide information, emotional support, social support, entertainment or link users to other humans or machines [45]. Customer service is a domain where chatbots have achieved strong and growing interest [46]. The renewed interest in chatbots is also partly driven by developments within E-Commerce and E-service to include Natural Language Interfaces [47]. In Norway, there is a change in how customers are offered assistance. Chatbots are gradually becoming a regular function in customer service platforms in banks, insurance, consulting and industry.

The humanlike conversation of chatbots gives customers the opportunity to type questions, and in return get meaningful answers to those questions in everyday language [48]. Chatbots can thereby be used to handle many routine queries which basically make up most service requests [46]. Furthermore, chatbots never require vacation, get grumpy or tired. According to Brynjolfsson and McAfee (2017) [49], the initial step of listening and understanding will be the hardest part of automating customer service.

Chatbots have also been proven useful in other domains. Within the health domain, chatbots have been evaluated favorably in comparison to search engines and information lines in answering adolescent's questions to alcohol, drugs and sex [48].

A study in the educational domain found that students were overwhelmingly positive to use chatbots as a means for learning and practice of a foreign language [50]. Recently, the use of chatbots have been discussed in the domain of human resources services, as a way of recruiting candidates for jobs, supposedly facilitating the recruitment process [51]. Although chatbots are the object of a recent surge of interest, chatbot research and development dates back to the 1960's [52]. The renewed interest is largely attributed to two developments. The developments within machine learning and artificial intelligence (AI) made chatbot applications easier to train and implement as a result of strengthened capabilities in identifying user intents and sentiments, and improved Natural Language Processing [53].

Furthermore, chatbots have gained renewed interest as a result of changes in the popularity and availability of messaging platforms. This channel allows businesses reach out to their target audience anytime anywhere via platform such as WhatsApp, Slack, Facebook Messenger or WeChat [54]. As they grow numerous on messaging platforms and implemented as virtual assistants by some technological companies, the use of chatbots is slowly becoming part of people's daily lives [50]. Chatbot technology has been incorporated into different online environments like E-Commerce, delivery services and Daily News. Lately, there has been a substantial growth in developing chatbots for marketing and customer service [54]. Servion [55], recently predicted 95% of all customer support service interactions to be handled by AI-applications within 2025, including live telephone and online conversations.

The current and predicted impact of chatbots and AI-applications in customer service illustrates the fast-growing change that makes it essential to gain knowledge about how chatbots are used and perceived by users. In spite of the early optimism concerning the launch of chatbot technologies by Facebook and Microsoft, theorists noted user adoption of chatbot applications to be less substantial than hoped [56]. The potential of chatbots have seemingly not yet been realized as expected by the technology industry. One reason might be that many chatbots currently on the market have failed to fulfil user's needs due to a relatively high frequency of meaningless responses, unclear purposes or insufficient usability [57]. Lack of user focus by developers seems to be prominent.

2.7 Empirical studies

Previous research studies focused mainly on web-based chatbot applications that were accessed through a computer or a laptop. From the '60s onwards, chatbot applications were originally used for entertainment using basic keyword match techniques to respond to user inputs [58]. Since then, research studies have been carried out on Natural Language interfaces and texts, and various architectures for chatbot applications have been developed [58]. Research by Mott [59] states that chatbot software may be used in businesses enterprise to help in customer service, help desk, technical support and guided selling. Their research study concentrated on application of web-based virtual agents and technical problems regarding the design and deployment on massive scale. They stated that conversational virtual agents need a good language processing capability. For the agents to be deployed on a large scale, they should be reliable, secure, and interoperable within existing IT infrastructure.

In addition to studies by Mott [58][59], they stated that besides commerce, chatbot applications can be used for language learning, entertainment, and in education as also shown by Kerly [60], who studied the way chatbot applications may be used as a negotiation in education as in aid for students. Additionally, the virtual agents may be utilized in healthcare industry as expressed in research study by Bickmore [61], who presented a virtual health counselor. Several research studies discussed recommendation virtual agents [62]; programs to assist in recommending consumers when making decisions while shopping online. Shopping bots are also well researched. They are bots designed to help customers in comparing and shopping products online [63][64]. Atwell [58] reviewed the importance of chatbot application in multiple domains like education and E-Commerce and inferred that chatbot programs should not replace nor imitate a conversation with humans. They believed that chatbot application should be designed as a tool to help people. Using natural language should ease HCI.

A recent research study [65], described an approach on implementing a web-based AI chatbot application which could operate as digital virtual assistant in scheduling meetings. However, the interaction happened through e-mail messages. There are research studies [66][67], which proposed measures to assess chatbot applications. As these AI applications expands to the messenger interfaces, we need a different research technique to measure their acceptance in telecommunication industry.

2.8 Analysis of Chatbot Implementation

Chatbot applications can be used to automate firm's internal business process and customer interactions. These applications are powered by AI and use NLP for communicating with humans either through voice or text. This subsection will discuss the status of chatbot implementation globally, regionally and in Kenya.

2.8.1 Chatbot Implementation Globally.

Recently, the industry and political institutions have expressed strong and growing interest in AI, with AI research and application programs rapidly growing globally. The industry is focused on future uses of Artificial Intelligence. As stated by a report [68] that was provided by Venture Capital Corporation Insights (VCCI) in United States in July of 2016, Google, Intel, Microsoft, Apple, Twitter and other IT giants have acquired approximately 140 financial firms in Artificial Intelligence field since 2011.

In the first half of 2016, investments in AI exceeded that discovered in 2015, and about 200 artificial intelligence related firms raised above $1.4 billion in stock market. A significant number of mergers along with flood of capital, are expediting integration of artificial intelligence technologies in applications, thus increasing the fast evolution of related economy. For instance, Google created an uproar after purchasing the neural network firm called DNNresearch ultra-expensively in 2013 [69].

Deep learning is the latest technology in the industry and has enabled Google enhance precision of picture searching. Deep learning is the main technology linked with Unmanned Ground Vehicles (UGV) and Google Glass [70]. Google has been developing applications from mobile first toward AI first. The integration of artificial intelligence with firms demands created significant shift in the mode of service delivery. For instance, Xiaobing is a chatting robot developed by Microsoft, has been steering transformation from traditional GUI to interactive interfaces with emotional understanding and natural language [71].

In June of 2016, Microsoft obtained LinkedIn and reconstructed the Internet community with use of AI technology. Additionally, the Watson application [72] which was developed by IBM is being used in hospitals in screening hundreds of millions of patient records to find history of cancer treatment. It provides recommendations to diagnose leukemia and gives therapeutic schedules thus modifying the paradigm of oncotherapy and clinical diagnosis.

Nowadays, people connect and converse virtually via messengers and chatbot technology is the foundation of this connections. The leading artificial intelligence powered chatbot applications include; Bold 360, LivePerson, Watson Assistant, Ada, Inbenta, Vergic and Rulai.[73] In early days, chatbot applications were developed to converse with people over the internet. This technology was limited to people who wanted to connect and have social conversations. However, current trends show that majority of companies are now using AI chatbot when communicating to their customers, respond to queries and receive feedback [73]. The AI chatbot responds like a real human due to combination of ML and predefined scripts.

Chatbot application responses are defined by the underlying software and access to knowledge database. Apple's Siri, Amazon's Alexa, and Samsung's Bixby, can provide information on latest news and weather conditions [73]. E-commerce companies focus on using chatbot applications to delight their CX. The adoption of chatbots globally has been rising as businesses recognize the usefulness of offering great CX which is cost effective and personalized [74].

2.8.2 Chatbot Implementation Regionally

In Nigeria, AIICO Ella is a chatbot application for insurer running on Facebook Messenger and web. It provides customer support with live human customer care call center agents. The application helps customers shop and purchase auto within seconds [75]. Rule-based chatbot applications are used in the banking sector. The UBA bank uses LEO, Diamond bank uses Ada, Stanbic IBTC uses Sami, Access bank uses Tamara.

These chatbot applications are used in performing simple daily banking operations like airtime purchase, stock trading, bills payment, conversing with a customer and transfer of money via social network [76]. The Rwandan government, for example, started using Chatbot Babyl, which is capable of relieving medical doctors from dealing with simple medical inquiries and refer only advanced and serious cases [77].

2.8.3 Chatbot Implementation in Kenya

There is increased uptake of chatbot applications locally, for instance, UBA Kenya's Leo, Safaricom's Zuri, and Jubile Insurance's Julie. These applications perform several functions including digital sales, transactional queries and customer support [78]. Local adoption is slow due to little understanding of how AI chatbot application can bring value to business. Nowadays, consumers buy experiences instead of products and services. AI chatbot can help businesses offer personalized experiences because they make conversations interactive, relevant and engaging. Additionally, some farmers in Kenya utilizes Arifu chatbot application to learn about agronomy and finances. It offers free educational content from credible sources and organizations about farming to farmers via SMS [79]. Some examples of chatbot applications under development include; Bot Auditor, Insurance Bot, Business Registration Bot, Book Slot Bot, Approval Work Bot and Leave Management Bot [80].

III.Methodology

The study used mixed method to establish the relationship between AI chatbot adoption and telecommunication industry. This design was applied in previous research studies and revealed to be effective and efficient in describing relationships between different attributes. The research adopted Delphi technique. In Delphi method, the researcher reaches out to experts in the area of the study. This method is useful in gaining an in-depth knowledge of the issue being researched on. This research employed descriptive survey in order to achieve research study objectives.

Descriptive survey was appropriate in determining implementation status of AI chatbots in telecommunication industry. The focus of the study was to identify key metrics that will eventually guide the researcher develop a framework that could be used as a guide for adoption of AI chatbot application in the telecom firms. The study employed expert opinion in validating the proposed adoption framework. Expert opinion is an interpretation by specialists or experts with experience in a particular area about a scientific evidence concerning that specific topic and in evaluation of products. The research study adopted this technique in order to validate the developed research model.

3.1 Location of the Study

The research study was carried out in two telecommunication firms in Kenya which have a higher percentage of market share. The firms are identified as firm's X and Y for the purpose of this study and in keeping anonymity of the firms.

3.2 Target Population

Target population is a whole group of individuals from which research study data is obtained and conclusions made. The target population were experts in the field of artificial intelligence in two telecommunication firms in Kenya. For study purposes, AI technologies included, NLP, Machine learning, chatbots and voice recognition.

3.3 Sampling.

Saunders [81] defines a sampling design as the technique that researchers use to select a subgroup from the total population which will be involved in the study. It acts as a guide to help the researcher determine how the study samples will be selected from the study population. Purposive sampling was applied in the study. It is non-random sampling procedure where the members of target population who meet a certain criterion are chosen, in this case, AI experts in the selected telecom firms were chosen. The study involved physically visiting the selected telecommunication industries, explaining the purpose of the visit to helpdesk team, who later connected the researcher to the IT team lead. After the IT team lead understood the purpose of the study, he selected from IT team, AI experts who participated in the study.

IV.Data Analysis and Presentation

Table 4.1 Reliability Test

Variable	Cronbach alpha
Organizational Factors	0.871
Technological Factors	0.761
AI chatbot adoption	0.891

The findings showed the recommended Cronbach's Alpha above 0.70 was achieved for internal consistency of data after testing all variables [82]. The validity of data is extent by which the test measures what it is expected to measure [83]. Mugenda [82] describe validity as extent to which the research study findings attained from data analysis, represents the phenomenon under study. In agreement with Table 4.1, Kaiser –Meyer -Olkin, the measure of sampling sufficiently denoted KMO value above 0.5, thus sample size was adequate to consider the data sample as normally distributed. The KMO value that is greater than 0.5, is sufficient to treat data as distributed normally.

The Bartlett's Test Sphericity tested null hypothesis item to item correlation matrix. Based on received data from participants for all effective variables, was identity matrix. The Bartlett's Test was analyzed via Chi-Square and presented as in Table 4.2. All variables were significant at 5% significance level, signifying that the null hypothesis is declined.

Table 4.2 Test for Validity

Factors	**KMO test**	**Bartlett's test of sphericity**		
		Chi-Square	df	Sig.
Organizational Factors	.906	221.26	4	0.000
Technological Factors	.907	340.74	4	0.003
AI Chatbot adoption	.891	334.70	4	0.002

Extraction Method; Principal Component Analysis.

4.1 The Relationships

This strived to establish Correlation Analysis relationship between variables of research study, that is: Organizational Factors, Technological Factors and AI Chatbot Adoption. The findings of Correlation Analysis are indicated in Table 4.3.

Table 4.3 Correlation Analysis

		Organizational Factors	**Technological Factors**	**AI Chatbot Adoption**
Organizational Factors	Pearson Correlation	1		
	Sig. (1-tailed)			
	N			
Technological Factors	Pearson Correlation	.634*	1	
	Sig. (1-tailed)	.001		
	N			
AI Chatbot Adoption	Pearson Correlation	.306	.146*	1
	Sig. (1-tailed)	.095	.020	
	N	**20**	**20**	**20**

*. Correlation is significant at the 0.05 level (1-tailed).

The research study results in table 4.3 showed that a strong positive and significant relationship between organizational and technological factors exist. This was portrayed by a Pearson Correlation Coefficient of, r = 0.634, p-value = 0.001 < 0.05, significant at 0.05 level of significance. This meant that improving on organizational factors would lead to more comfortable and easy use of new technology in telecommunication industry. The results in table 4.3 shows that there was a strong positive but non-significant relationship between the organizational factors and the adoption of chatbot software in customer support services with a

Pearson Correlation Coefficient of, r =0.306, p-value = 0.095 > 0.05, not significant at 0.05 level of significance. There was a non-strong positive but significant relationship between technological factors and adoption of chatbot software with a Pearson-Correlation Coefficient of, r = 0.146, p-value = 0.02< 0.05, that is significant at 0.05 significance level. This implies that use of technology in an organization directly relates to the adoption and use of chatbot software in customer support services.

4.2 The Regression Analysis

ANOVA test was used in determination of whether the developed model is essential in predicting the adoption and usability of AI Chatbot software in telecommunication companies/organizations in Kenya. From the analysis of findings in table 4.4, the value of R-Square is 0.613. This implies that, 61.3% of the variation of AI Chatbot adoption in an organization was explained from the Organizational and Technological factors in the telecommunication firms under the study.

Table 4.4 The Model Summary

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.783[a]	.097 .613	.009	1.32284	.613	.915	2	17	.003

a. Predictors: (Constant), Technological factors and Organizational factors

b. Dependent Variable: AI Chatbot Adoption

At 0.05 significance level, ANOVA test showed that independent variables namely, Organizational factors and Technological factors, were both predictors of the adoption of AI Chatbot software in the telecommunication industry in Kenya in this model. In table 4.17, the ANOVA test analysis is shown by a p-value = 0.003, that is less than 0.05 level of significance (p-value = 0.003 < 0.05).

Table 4.5: The ANOVA Table

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	3.202	2	1.601	.915	.003[b]
	Residual	29.748	17	1.750		
	Total	32.950	19			

a. Dependent Variable: AI Chatbot Adoption

b. Predictors: (Constant), Technological factors and Organizational factors

Table 4.6: The Regression Coefficient

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	5.022	2.290		2.192	.043
	Organizational factors	.783	.261	.356	1.195	.248
	Technological factors	.009	.033	.080	.268	.792

a. Dependent Variable: AI Chatbot Adoption

From the results in Table 4.6 above, at 0.05 significance level, the connection between the dependent and independent variable is as shown in the equation below

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon \text{ ……………………………….… } (4.1)$$

Here, the Y value represent the AI Chatbot Adoption, X_1 represent the organizational factors, X_2 represent the technological factors, and ε value stands for the error term in the model

Therefore, using the Regression Coefficient in Table 4.18, we get;

$$Y = 5.022 + 0.783 * X_1 + 0.009 * X_2 + \varepsilon \text{ …………………..… } (4.2)$$

The equation shown above, shows that an increase by one unit in organizational factor, the AI Chatbot adoption in an organization will increase by 0.783. A unit increase in the technological factor will increase the AI Chatbot adoption by 0.009.

4.3 Analysis of Intervening Effects

It was vital to investigate whether government regulation, need for automation and customer pressure intervened AI chatbot adoption. To determine the effects of intervening variables, multiple R^2 and Beta weights were used. The Beta value should be greater than 0.1, and if the value is above 1, then it shows multi-collinearity. The scale used were as follows;

i. A small effect is indicated by a Beta value between 0.1 and 0.2.
ii. A medium effect is indicated by a better value between 0.3 and 0.5.
iii. Values above 0.5 indicates a large effect.
iv. Values less than 0.1 indicates no effect.

OF = Organizational factors
TF = Technological factors
GR = Government regulation.
NA = Need for automation
CP = Customer pressure

Table 4.7 : Intervening Effects

	R^2	Beta	Significance
OF + GR + NA	0.025	0.502	0.285
OF + GR + CP	0.084	0.384	0.012
OF + CP + NA	0.029	0.356	0.328
TF + GR + NA	0.006	0.521	0.478
TF + GR + CP	0.013	0.121	0.903
TF + CP + NA	0.017	0.016	0.129

The results in table 4.7 indicated how the different intervening factors such as government regulations, need for automation and customer pressure affect dependent variable in this research study. Government regulation and need for automation had a large effect on organizational factors as shown by a Beta value of 0.502. Customer pressure and government regulation had a medium effect on organizational factors as indicated by a Beta value of 0.384. The need for automation and customer pressure had medium effect on organizational factors as shown by a Beta value of 0.356. The need for automation and government regulation had large effect on technological factors as indicated by a Beta value of 0.521. Customer pressure and government regulations had a small effect on technological factors as indicated by a Beta value of 0.121. The need for automation and customer pressure had no effect on technological factors as indicated by a Beta value of 0.016.

V. Discussion and Framework

The study indicated that the adoption of AI chatbot technology for real-time customer care service support is influenced by organizational factors, technological factors and intervening factors. The factors identified were in correlation relationship with each other. Based on results of data analysis, nine distinct AI chatbot adoption factors were identified that will influence adoption of AI chatbot technology in customer care support service provision in telecommunication industry. These factors are:

i. **Perceived benefits:** It's the perception of positive consequence or feedback as a result of adopting chatbot for real-time customer care support for instance, cut costs, create better CX, and real time support i.e. perceived usefulness.

ii. **Top management support:** It is the support from executives who translate policies into goals. They make decisions which affect everyone in the firm. They fund an innovation.

iii. **Organizational readiness:** It is the organizational preparedness to implement a new innovation. Readiness in terms of willingness to implement chatbot technology, and being ready with both IT and financial resources.

iv. **Compatibility:** It is the capacity for two systems to work together without having to be altered to do so, for example, AI chatbot and human customer care representatives support infrastructure.

v. **Complexity:** It is the simplicity or difficult of a system while using it. The system that is simple to use tend to be accepted easily while a system that is difficult to use is easily rejected i.e. ease of use.

vi. **Technology availability/readiness:** It is individual's tendency to embrace a new technology for fulfilling in home life or work. The new technology must be available with support infrastructure and must be secure and reliable.

vii. **Customer pressure:** It's the pressure from customers who need prompt and frequent feedback when they make customer care support service requests. The need for automation comes as a result of competition from other industries that are adopting new innovations for their daily business operations.

viii. **Need for automation:** The company's willingness to automate some functions in its operation.

ix. **Government regulation:** The regulations given by the government on how a company should perform its functions.

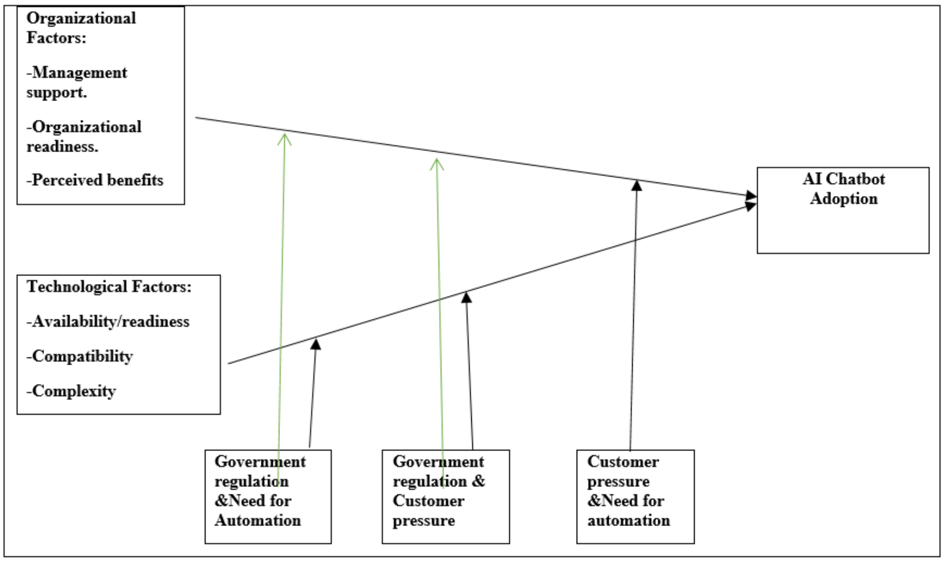

Figure 4.2: AI Chatbot Adoption Framework

VI. CONCLUSION

The researcher discovered that AI chatbot technology is implemented to a small extend. The results confirmed that telecom firms were ready to adopt the AI chatbot technology. The new technology is believed to enhance customer insights and cut costs as fewer human customer care representatives will be required as a result of automation. The AI chatbot technology should be less complex and compatible. The benefits that come with adoption of this AI chatbot technology include cost cutting and saving on time as long waits while calling or messaging will be significantly reduced since the application can respond to many customers at once.

Based on the findings of the study, the framework developed can be used as a guiding principle, to guide stakeholders in adoption of AI chatbot technology in telecommunication industry. The adoption will ensure that customers do not spend significant amount of time to get solutions to their requests, which will result in better customer experience.

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