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Chatbot Adoption Framework for Real-Time Customer Care Support

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ABSTRACTS

In our society today, most sectors are digitizing and automating their processes for efficiency. Human labour has become obsolete as a result of the disruption of labour markets brought about by the rising complexity and availability of software programs. When seen in this light, the adoption of artificial intelligence chatbots by businesses as a supplement to human customer service representatives serves as a crucial development. Computer programs or software that communicate with humans using natural language are referred to as chatbot applications. Through the use of speech, text, or both, the purpose of a chatbot is to simulate human interaction in response to input in natural language. For the purpose of providing customer care support services, there are no well-formulated rules for the implementation of artificial intelligence chatbots in Kenyan telecom companies. An adoption framework for the deployment of artificially intelligent chatbots in the telecommunications sector was proposed as the objective of the research. This was accomplished by determining the current level of the installation of chatbot apps in Kenya and identifying the primary metrics that might be used as indications for the dissemination of chatbots. A study of the earlier

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frameworks and models on technology adoption was conducted in order to determine the relevant metrics. A combination of research approaches was used in this study, with questionnaires and interview schedules being used to obtain quantitative and qualitative data, respectively. In order to examine qualitative data, content analysis was what was used. Using tables and charts, descriptive analysis was performed on the quantitative data, and the findings were presented. AI specialists working for Safaricom PLC and the Communications Authority of Kenya were the ideal candidates for this position. From the two different telecommunications companies, a sample was selected for the research study utilizing the Delphi approach. A descriptive analysis as well as a major component analysis were used because they serve as a guide on aspects to consider before using AI chatbots for customer support services provision. The results of this research are particularly important to all companies that are involved in providing telecommunication services.

1. INTRODUCTION

Machines, and more specifically computer systems, are capable of displaying intelligence, which is referred to as artificial intelligence (AI). In this subfield of computer science, researchers seek to understand how to program computers to sense their environment, analyse that data, and then use that data to take actions that increase their likelihood of successfully completing predefined tasks (Russell & Norvig, 2021). One term for these kinds of robots is artificial intelligence.

Some prominent uses of artificial intelligence include advanced web search engines like Google Search, recommendation systems used by YouTube, Netflix, and Amazon, voice-activated assistants like Siri, Google Assistant, and Alexa, autonomous vehicles like Waymo, tools for creativity and generative art like Apple Intelligence and ChatGPT, and games where players use strategy like chess and go. Nevertheless, a great number of applications of AI are not considered to be AI: "A significant amount of cutting-edge artificial intelligence has made its way into broad applications, often without being referred to as AI. This is due to the fact that as something becomes more useful and widespread, it is no longer referred to as AI." (Gere, 2023; Kaplan & Haenlein, 2020).

Alan Turing was a pioneer in the field of substantial studies in the field that he developed and named "machine intelligence" (Copeland, 2004). John McCarthy, Marvin Minksy, Nathaniel Rochester, and Claude Shannon are

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generally acknowledged as the most influential pioneers in the subject of artificial intelligence. They were the ones who initiated the academic discipline of artificial intelligence in the year 1956 (Copeland, 2004; Friendly, 1974; Kaplan, 2022). There were several periods of optimism in the field (Marquies et al., 2020; Russell 1988). which were then followed by periods of disappointment and limited funding, which are collectively referred to as the "AI winter" (Russell, 1993; AI, 1993). When deep learning beat all preceding artificial intelligence approaches in 2012, funding and interest in the field skyrocketed. This trend continued after 2017 with the development of the transformer architecture, which further fuelled the growth of the field (AI, 1993; AlexNet, 2018). Companies, institutions, and laboratories that were mostly headquartered in the United States were the driving force behind significant advancements in the area of artificial intelligence Kothari, 1978 (Toews, 2023). As a result, the AI boom that occurred in the early 2020s had materialized.

During the past few years, the exponential growth of artificial intelligence has had a significant impact on a variety of economic and social factors. These factors include shifts in the nature of work, the role of government and healthcare systems, the prevalence of data-driven decision-making, and the pervasiveness of AI systems across a wide range of industries and fields of study. Discussions on legislative and regulatory frameworks to guarantee the security and advantages of AI are prompted by issues over the ethical implications, hazards, and long-term impacts of the technology.

Specific aims and methods give rise to the many branches of AI study. Knowledge representation, reasoning, planning, learning, vision, NLP, and robotics assistance are some of the more conventional aims of artificial intelligence research. An objective of artificial intelligence research is to create systems that can perform at least as well as humans at any given job (Frank, 2015).

Artificial intelligence (AI) researchers have used a diverse array of strategies to accomplish these aims. These include formal logic, mathematical optimization, artificial neural networks, statistics, operations research, economics, and search procedures. Machine learning also incorporates ideas from philosophy, neurology, psychology, and linguistics. (Russell & Norvig, 2021).

2. FUNDAMENTAL CONCEPTS OF ARTIFICIAL INTELLIGENCE (AI)

2.1. Machine Learning

Statistical algorithms that are able to learn from data, generalize to new data, and carry out tasks independently, without the need for human involvement are what are referred to as machine learning (ML) in the field of artificial intelligence (AI) (Russell & Norvig, 2021). A lot of older methods have been outperformed by artificial neural networks (ANN) as lately cited (Kufel et al., 2023). Machine learning (ML) has several potential uses, such as in computer vision, medical imaging, email filtering, voice recognition, agriculture, and natural language processing (Hu et al., 2020; Yoosefzadeh et al., 2021). It is called predictive analytics when it is used to solve issues in a commercial setting. While computational statistics is not the

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only place where machine learning finds its techniques, it is a significant one.

Optimisation and mathematical programming give the mathematical underpinnings of ML. A related area of research known as data mining employs unsupervised learning to do exploratory data analysis (Bishop et al., 2006). Tom M. Mitchell defined the algorithms studied in machine learning as follows: "A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, improves with experience (Friedman, 1998). This definition has been widely quoted. In place of a cognitive description, this list of ML-related activities offers a fundamental operational definition. So, this is in line with what Alan Turing suggested in his "Computing Machinery and Intelligence" article. Instead of asking, "Can machines think?", he asks, "Can machines do what we; as thinking entities can do? (Mitchell, 1997).

There are two main goals of modern ML. One is to use models to categorize data. Second, using these models to forecast future events is the goal. Training a hypothetical data classification system to recognize cancerous moles might be accomplished by the use of computer vision of moles in conjunction with supervised learning. The trader may be able to learn about prospective future forecasts from a ML system that is used for stock trading (Harnad & Scherzer, 2008). The AI chatbot to be adopted in telecom firms should use ML to learn from past experiences to predict the future when used in customer care support service provision.

2.2. Natural language processing (NLP):

Natural language processing, sometimes known as NLP, is a specialization within the fields of computer science and artificial intelligence. The fields of knowledge representation, information retrieval, and computational linguistics, which is a subfield of linguistics, are all closely related to it since their primary focus is on providing computers with the ability to read content that is stored in natural language. Data for machine learning and deep learning is usually culled from text corpora using statistical, rule-based, or neural-based methods.

Text categorization, voice recognition, NLP comprehension, and NLP production are some of the mainstays of NLP. A rudimentary form of NLP emerged in the 1940s (Carradini, 2024). Alan Turing first suggested the Turing test—now known as an intelligence criterion—in a paper titled "Computing Machinery and Intelligence" published in 1940. However, the issue of intelligence was not explicitly stated as distinct from AI at that time. An automated job involving the interpretation and synthesis of natural language is included in the proposed exam. Telecom firms should adopt a chatbot can read, process and respond to text or voice in natural language without escalating the conversation.

2.3. Natural language understanding (NLU)

An area of AI known as natural language understanding (NLU) or NLI studies how computers comprehend human written language (Patrut, 2013). NLU is supposedly a challenging area for AI researchers to tackle (Semaan, 2012). Applications that have piqued the attention of businesses include

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autonomous reasoning, machine translation, question answering, news collection, text classification, voice activation, archiving, and large-scale content analysis (Louisville, 2024). There are a few commonalities throughout most NLU systems, regardless of methodology (Sandewall, 2008). The system can't parse sentences into their component parts without a language vocabulary, parser, and grammar rules (Macherey et al., 2021). Building a comprehensive lexicon with an appropriate ontology is no easy feat; the Wordnet lexicon, for instance, was the product of many man-years of labor (Hircshman & Gaizauskas, 2021).

Semantic theory is also required for the system to facilitate understanding. The semantic theory that a language-understanding system employs determines its interpretation capabilities. When it comes to building computer-automated semantic interpretation, competing theories of language have their advantages and disadvantages (Lawler & Dry, 1998). A few examples include pragmatics, which uses context to infer meaning, and naïve semantics and stochastic semantic analysis (Lawler & Dry, 1998; Dahlgren, 1998; Mason, 2001). In order to formalize the meaning of texts written in natural language, semantic parsers (Ward, 1991).

Additionally, more complex NLU applications aim to build logical inference into their structure. In most cases, this is accomplished by creating a collection of predicate logic statements from the derived meaning and then drawing inferences from them via logical deduction. There is a common practice among logic-oriented systems, such Prolog-based ones, to expand upon the internal logical representation framework (Wong & Mooney, 2006; Covington et al., 1994). Systems developed on functional languages, like Lisp, need their own system to make logical statements. Within the realm of natural language understanding (NLU), context management may provide its own set of challenges. In response to a broad variety of examples and counterexamples, a variety of modeling approaches for the formalization of context have arisen, each of which comes with its own set of benefits and drawbacks (Melish, 1989; Dyer, 2020).

The chatbot adopted in telecom industry should be able to read and understand natural language. A good example of this would be if a chatbot were to have a discussion with a client, and the consumer said that they had a stinking foot and a runny nose. In order to avoid escalating the discourse, the artificial intelligence chatbot should refrain from declaring that the feet are intended to run and the nose should sniff. It should be possible for the chatbot program to comprehend the discussion in the same way that a human participant can.

2.4. Human-computer interaction (HCI)

The study of how humans interact with computers, more especially how they use and construct computer technology, is the subject of the academic discipline known as human-computer interaction (HCI). Research is conducted by academics in the field of human-computer interaction (HCI) to investigate the behaviours that people engage in while dealing with computers and to create tools that assist individuals in accomplishing new tasks. One term for

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any device that lets people talk to computers is a "Human-computer Interface (HCI)".

Located at the crossroads of several academic disciplines, hybrid HCI encompasses areas including design, media studies, computer science, behavioural sciences, and more. After writing "The Psychology of Human-Computer Interaction" in 1983, Stuart K. Card, Allen Newell, and Thomas P. Moran brought the phrase to a wider audience. It wasn't until 1975 when Carlisle made the first known usage (Thomason, 2001). The idea behind the word is to show how computers are more versatile than other tools and how they encourage interaction between the user and the machine that doesn't have a prescribed agenda. For theoretical purposes, the idea of conversation is fundamental because it draws parallels between human-to-human and human-computer interaction (Carlisle, 1976; Suchman, 1987).

The interaction between computers and humans is known as the human-computer interface. Interaction loops are described as the flow of data between humans and computers. Multiple components make up the interaction loop, including: Human-Computer Interaction Built on Visuals —— Analysing Expressions on Faces: Here, the emphasis is on reading people's emotions from their expressions on their faces.

The focus of researchers in this field is the monitoring and analysis of large-scale bodily motions. A common method of direct user-computer interaction in command-and-action situations is gesture recognition, which entails detecting and understanding user-produced movements. While the particular aims of each domain differ according to applications, they all work together to improve HCI. One domain is gaze detection, which entails monitoring the user's eye movement. This is done mainly to gain insight into the user's attention, intent, or focus in context-sensitive scenarios. It is worth mentioning that visual techniques have been investigated as potential substitutes or augments for other interaction kinds, including those based on audio and sensors. To rectify speech recognition mistakes, for instance, lip reading or lip movement tracking has been beneficial.

Audio - Based HCI ----Human-computer interaction (HCI) relies heavily on audio-based interaction, which processes data obtained from a variety of auditory sources. The information provided by auditory signals is often quite trustworthy, important, and even unusually illuminating, even if their nature is less varied than that of visual signals. Some of the fields that fall within this umbrella of study are: The field devoted to the detection and understanding of spoken language is known as speech recognition.

Academics working in the field of speaker recognition primarily aim to find ways to differentiate between various voices. Emotional Cues in Audio Signals: Some have attempted to integrate human emotions into smart human-computer interaction via the use of auditory emotion analysis. Emotion analysis and

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the development of smarter HCI systems are both aided by human-made noise/sign detections, which include the identification of common human auditory signals such as sighs, gasps, laughter, screams, etc. One emerging field in human-computer interaction is musical interaction, which has potential uses in the creative industries and entails creating and interacting with music. Both visual and auditory HCI systems investigate this area.

Digitizers and motion tracking sensors: state-of-the-art gear that has changed the game for sectors including gaming, animation, art, and cinema. More immersive computer-reality interactions are possible with the use of these sensors, which may take several forms, such as wearable fabric or joint sensors. Sensors that detect touch are haptic, which makes them useful in many contexts, but especially in robotics and VR. Important in medical operations and for making humanoid robots more sensitive and aware, they are indispensable. Sensors that measure the force of an applied force on a surface are also useful in robotics, VR, and healthcare.

Although it hasn't received as much attention as other fields, research on taste and smell sensors has been ongoing. A few of these sensors are rather advanced, while others are still in their early stages of development.

The chatbot app to be adopted should have a simple and flexible interface to have a smooth interaction during engagement.

2.5. Empirical studies

Empirical studies on chatbots explore various aspects, including their effectiveness, user satisfaction, design considerations, and applications across different sectors. Here are some notable empirical studies on chatbots. There was a study of the impact of chatbot use on customer satisfaction and understanding chatbot users. This study investigated how chatbot use affects customer satisfaction in e-commerce. It provided insights into how different chatbot features impacted user experience and satisfaction (Dourish, 2021). There was a study on, "The impact of chatbots on customer service: Evidence from the Financial Services Sector" This empirical study examined the impact of chatbots on customer service in the financial industry, focusing on user satisfaction and service efficiency (Zhang & Zheng, 2019). In addition, there was a study on "Designing Chatbots for Effective Human-Computer Interaction: An Empirical Study of the Chatbot's Interaction Design"

This study explored design principles and usability considerations for chatbots, providing empirical evidence on what makes a chatbot effective and user-friendly (Liu & Li, 2020). A study was conducted on, "The Effect of Chatbot Design Features on User Experience: An Empirical Study" This research examined how various design features of chatbots affect user experience and satisfaction (Chai & Tan, 2019). There

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was a study on "Evaluating the Effectiveness of a Health-Related Chatbot for Symptom Checking and Health Information" This study assessed the effectiveness of a chatbot designed to provide health information and symptom checking, focusing on accuracy and user satisfaction (Ramo & Lewis, 2020; Kopp, 2018). A study was carried out on, "Chatbots for Mental Health Support: An Empirical Study of User Engagement and Outcomes". This study explored the use of chatbots for mental health support, analysing user engagement and the impact on mental well-being (Ramo & Lewis, 2020). A research study was done on, "The Effectiveness of Chatbots in Educational Settings: A Review of Empirical Studies". This review paper summarized empirical studies on the use of chatbots in educational contexts, highlighting their effectiveness in enhancing learning experiences (Firth & Tourus, 2020). There was research on, "Chatbots as Learning Tools: An Empirical Study of Their Impact on Student Engagement and Learning Outcomes" This study investigated how chatbots impact student engagement and learning outcomes in higher education (Al-Azawei & Alowayr, 2020). There was a study on, "Challenges in Deploying Chatbots: An Empirical Analysis of Common Issues and Solutions" This paper discussed the common challenges faced when deploying chatbots and provides empirical insights into effective solutions (Johnson & Johnson, 2019). Lastly, a study was conducted on, "Understanding the Limitations of Chatbots in Customer Service: An Empirical Study" This study investigated the limitations of chatbots in customer service scenarios and their impact on user satisfaction (Salehahmadi & Goodwin, 2020).

These empirical studies provide a comprehensive view of various aspects of chatbots, including their effectiveness, design, applications, and limitations. They are valuable resources for understanding how chatbots can be optimized and utilized across different domains.

2.6. Chatbot implementation

Applications of artificial intelligence chatbots may be used to automate the internal business processes of a company as well as communications with customers. These apps are driven by artificial intelligence and make use of NLP to communicate with people via voice or text. A discussion of the current state of chatbot deployment on a global, regional, and local scale will be included in this subsection.

2.6.1. Global implementation

In the U.S., Siri is a chatbot developed by Apple which is a widely known virtual assistant integrated into iOS devices. It handles tasks like setting reminders, answering questions, and providing information (Mehta & K. Rakesh, 2020). Cortana or Microsoft's Cortana is a virtual assistant available on Windows devices, helping with tasks such as scheduling, reminders, and information retrieval (Aron, 2011). IBM Watson is a powerful AI chatbot used in

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various industries, including healthcare, finance, and customer service, for tasks ranging from data analysis to customer support (Yang et al., 2021).

In India, Haptik is a popular AI chatbot platform that offers customer support, information retrieval, and personal assistant services for various businesses (Murtaza et al., 2016). Riya developed by the Indian company, Zinnov, is a chatbot designed for the HR industry, helping with employee queries and HR processes (Kubekar & Singhal, 2020). Aindra Systems is a healthcare chatbot which assists with diagnostic support and patient interaction, focusing on improving healthcare delivery in India (Nguyen, 2024).

In China, Xiaoice developed by Microsoft China, is an advanced AI chatbot known for its conversational abilities and emotional intelligence, used for various applications including customer service and personal interactions (Yadav et al., 2023). DuerOS developed by Baidu, is an AI chatbot system used in smart devices and services across China for voice interaction and assistance (Thoutam & Jalasri, 2024). WeChat Official Account Chatbots: WeChat, a major messaging platform in China, supports numerous official account chatbots used by businesses, services, and government bodies to interact with users (Jais et al., 2024).

In Japan, Pepper developed by SoftBank Robotics, is a humanoid robot with conversational abilities, used in various customer service and hospitality settings (Yuan et al., 2021). Rinna developed by Microsoft Japan, is a chatbot known for its ability to engage in natural conversations and is used for social interaction and customer service (Nyongsea et al., 2020). AI Nurse is implemented in healthcare settings, this chatbot assists with patient inquiries and basic medical advice, aiming to improve healthcare efficiency in Japan (Sofiyah et al., 2024).

These chatbots showcase the diverse applications and advancements in AI technology across different countries.

2.6.2. Regional implementation of chatbots

In Nigeria, Ubenwa is a chatbot designed to provide maternal and child health support by analyzing a baby's cry to assess health conditions. It aims to improve healthcare delivery through AI technology (Bahera et al., 2024). Chuka is a chatbot used by Chuka University and some financial institutions to handle basic customer service tasks (Liu et al., 2020). The Nigerian Police Force Chatbot: This chatbot helps citizens report crimes and seek assistance from the Nigerian Police Force (Urbani, et al., 2024).

In South Africa, Moya which is Developed by the South African tech company, Botlhale, is a chatbot designed for general assistance and customer service (Anatriello et al., 2024). Bank Zero's Chatbot: Bank Zero uses chatbots to handle customer queries, process transactions, and provide information about banking services (Adam et al., 2021). Sizwe is a chatbot which helps users with healthcare-related questions

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and is part of the broader initiative to improve health service delivery in South Africa (Chakrabortty et al., 2022).

In Rwanda, Waka Waka is a chatbot which provides information and assistance related to public services and general inquiries for Rwandans (Ghosh et al., 2024). Gisagara is a local government chatbot designed to help residents of Gisagara District with information and services related to local governance (Alhammadi, 2023). E-Gov Chatbot developed by the Rwandan government, offers assistance with government services and information related to various public services (Rangert, 2024).

2.6.3. Local implementation of chatbots

Chatbots in Kenya are being used across various sectors, from customer service to healthcare and agriculture. M-Pesa Chatbot; M-Pesa, a popular mobile money service in Kenya, uses a chatbot to assist users with various queries related to transactions, account management, and service inquiries. This chatbot helps users navigate the M-Pesa ecosystem more efficiently (Ekechi et al., 2024). Hela: Health Chatbot; Hela is a health-focused chatbot developed to provide information and support regarding health conditions, symptoms, and medical advice. It aims to increase access to healthcare information in Kenya (Techweez, 2020). Aah! Chatbot; Aah! is a chatbot designed to assist users with financial literacy and savings tips. It is part of a broader initiative to improve financial inclusion and awareness in Kenya (Hela, 2021). AgroHub Chatbot; AgroHub provides agricultural information and support through a chatbot. It offers advice on farming practices, pest control, and crop management, helping farmers make informed decisions (Chatbot, 2021). Kenya Red Cross Chatbot; The Kenya Red Cross uses a chatbot to provide emergency assistance, disaster information, and first aid advice. It supports disaster management and response efforts by offering timely information to the public (AgroHub, 2021). Zuri is an AI chatbot designed to enhance customer service for various businesses in Kenya. It helps in automating customer support tasks, improving response times, and providing consistent service (Kenya, 2021).

Chatbots in Kenya are being implemented in various sectors including mobile money, healthcare, agriculture, and disaster management. These chatbots aim to improve access to services, enhance customer support, and provide valuable information.

3. METHODOLOGY

In order to determine the nature of the connection between chatbot adoption and the telecommunications business, the research was carried out using a combination of methods. This approach had been used in earlier research, and the results shown that it was successful in explaining the correlations that exist between a variety of characteristics. In this research, the Delphi approach was used. When using the Delphi approach, the researcher talks to people who are already knowledgeable in the field of the study. An in-depth familiarity with the studied subject can only be achieved by

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using this strategy. A descriptive survey was used to carry out this research and achieve its objectives.

For the purpose of determining the current state of chatbot deployment in the telecom business, a descriptive survey was the right method to use. The researcher built an adoption framework to help telecoms firms deploy chatbot applications. The focus was on identifying essential criteria that guided the development of the framework. For the purpose of validating the suggested adoption framework, the research used the opinions of experts. An interpretation of scientific facts about a particular subject and in the assessment of goods is what is meant by the term "expert opinion." This interpretation is provided by experts or specialists who have knowledge in a certain field. During the process of verifying the proposed adoption model, this approach was used in the research.

3.1. Location of the study

A greater proportion of the market share was held by two of Kenya's telecommunications businesses, which were the focus of the study. These industries were Safaricom PLC and Communications Authority of Kenya (CAK).

3.2. Target population

A complete group of people is referred to as the target population, and it is from this population that research data is collected and conclusions are drawn. Artificial intelligence specialists from Safaricom PLC and the Communications Authority of Kenya were the intended recipients of this message. For purposes of the study, artificial intelligence technologies included, chatbots, NLP, AI models, Machine learning, and voice recognition.

3.3. Sampling

The researchers use sampling as a design method to choose a subset of the population to be studied (Saunders, 2009). Afterwards, this particular section is included into the research. Researchers may use this method as a guide to choose representative samples from the population they're studying. The researcher used a technique called purposive sampling in this investigation. This method of non-random selection selects members of the target population based on whether or not they meet certain requirements. Here, the Communications Authority of Kenya and Safaricom PLC were chosen for their artificial intelligence expertise. A physical visit was made by the researcher to both of the telecommunications companies, and the researcher stated the cause for the visit to the helpdesk personnel. Through the helpdesk staff, the researcher was connected to the leader of the IT team. Following a briefing on the purpose of the research, the leader of the information technology team chose AI specialists who would later take part in this project.

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4. DATA PRESENTATION ANALYSIS AND DISCUSSION OF RESULTS

Table 1. Reliability Test

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

Following the testing of all variables, the results make it abundantly evident that the required Cronbach's Alpha value of 0.70 or above is attained for the purpose of ensuring the internal consistency of the data (Yin, 2013). Quantifying the degree to which a test measures its target construct is known as data validity measurement (Kothari, 1978). In accordance with Mugenda validity is characterized as the extent to which the research results correctly represent the phenomenon under study (Yin, 2013). It is reasonable to assume that the data sample follows a normal distribution as the sampling metric correctly indicated a KMO value greater than 0.5. This is in keeping with Table 4.1 provided by Kaiser – Meyer – Olkin. If the KMO value is more than 0.5, then it means that the data may be considered to be distributed regularly.

For the purpose of testing the null hypothesis, the Bartlett's Test Sphericity examined the item-to-item correlation matrix. Identity matrix was constructed on the basis of the data collected from participants for all of the effective factors. Chi-Square was used to conduct the analysis of the Bartlett's Test, and the results are provided in Table 4.2. There was a significant difference between all of the variables at the 5% significance level, which indicates that the null hypothesis is rejected.

Table 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

4.1 The relationships

The purpose of this endeavour was to use correlation analysis in order to ascertain the relationship between the study variables, which included technological features, organizational issues, and chatbot adoption. Table 4.3 displays the results of the correlation study, as seen in the image.

Table 3. Correlation Analysis

		Organizational Factors	Technological Factors	AI Chatbot Adoption
Organizational Factors	Pearson Correlation	1		
	Sig. (1-tailed)			
	N			

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		Organizational Factors	**Technological Factors**	**AI Chatbot Adoption**
Technological Factors	Pearson Correlation	.634*	1	
	Sig. (1-tailed)	.001		
	N			
AI Chatbot Adoption	Pearson Correlation	.306	.146*	1
	Sig. (1-tailed)	.005	.020	
	N	**20**	**20**	**20**

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

A strong and statistically significant association between technological and organizational factors is shown by the study's results, which are displayed in table 4.3. The presence of a p-value of 0.001 < 0.05 and a Pearson Correlation Coefficient of r = 0.634 suggests statistical significance at the 0.05 level. The findings show that improving organizational factors makes chatbot technology easy to utilize in the telecom industry. Table 4.3 shows that there is a strong and statistically significant relationship between the features of the company and the deployment of AI chatbots for customer assistance. The p-value is 0.005 < 0.05, indicating that the Pearson Correlation Coefficient is significant at the 0.05 level of significance, and the value of r is 0.306. The Pearson-Correlation Coefficient (r = 0.146) and p-value (0.02), both of which are statistically significant at the 0.05 level, demonstrate a strong positive association between technical factors and the adoption of AI chatbots. Consequently, a company's use of chatbots in customer assistance is intimately related to its use of technology.

4.2 The Regression Analysis

Adopting and employing chatbot software in Kenyan telecom firms was predicted using the defined framework. An ANOVA test was used to examine the significance of the test. Statistical examination of the data in table 4.4 yielded an R-Square value of 0.613. Furthermore, it was shown that 61.3% of the variability in chatbot adoption across telecom companies could be accounted for by technical and organizational variables.

Table 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	.783ª	.097 .613	.009	1.32284	.613	.915	2	17	.003

a. Predictors: (Constant), Technological factors and Organizational factors
b. Dependent Variable: Chatbot adoption

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b. Dependent Variable: Chatbot Adoption

Chatbot software usage in Kenyan telecom firms was shown to be influenced by both technological and organizational aspects, according to the ANOVA test. This was determined at a significance level of 0.05. In table 4.17, the findings of the analysis of variance (ANOVA) test are represented by a p-value of 0.003, which is below the threshold of significance of 0.05 (p-value = 0.003 < 0.05).

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

Table 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 data in Table 4.6 above, at 0.05 level of significance, the relationship between the independent and dependent variable is as indicated in the equation below

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon \quad (1)$$

In the equation, the Y value represents Chatbot Adoption, X1 represents organizational factors, X2 represents technological factors, and ε value represents the error term in the model Therefore, using the Regression Coefficient in Table 4.18, we get;

$$Y = 5.022 + 0.783 * X_1 + 0.009 * X_2 + \varepsilon \quad (2)$$

As seen by the equation presented above, an increase of one unit in the organizational component would result in a 0.783 percentage point rise in the adoption of chatbots in telecom companies. If the technology factor is increased by one unit, there will be a 0.009 percent rise in the usage of chatbots.

4.3 Moderating Effects

Investigating whether the introduction of chatbots was tempered by consumer demand, government regulation, and the need for automation was an essential step. We used a number of R2 and Beta weights in order to ascertain the impact of the moderating f

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factors. As a rule, the Beta value ought to be higher than 0.1, and if it is higher than 1, it indicates that there is multi-collinearity that exists. Following is a scale that was utilized;

- and 0.2 are Beta values indicating a small effect.
- and 0.5 are Beta values indicating medium effect.
- Large effects are shown by values above 0.5.
- No effects are shown by values less than 0.1.

OF = Organizational factors

TF = Technological factors

GR = Government regulation.

NA = Need for automation

CP = Customer pressure

Table 7. Moderating Effects

	R^2	Beta	Significance
OF + NA+GR	0.025	0.502	0.285
OF + CP+GR	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 findings shown in table 4.7 provide an indication of the many moderating variables that may have an impact on the adoption of chatbots in this research. These aspects include the need for automation, government regulation, and customer pressure from customers. As the beta value of 0.502 indicates, the need of automation and the regulation of the government have a significant impact on the variables that make up the organization. As shown by the Beta value of 0.384, the influence of customer pressure and government regulation on the variables of the organization is found to be moderate. Based on the 0.356 Beta score, it can be concluded that the demand from customers and the need for automation have a moderate impact on the factors of the company. Based on the 0.521 Beta value, it can be seen that the government regulation and the need for automation had a significant impact on the factors of technology. The 0.121 Beta figure demonstrates that the variables of technology were only marginally affected by the regulations of the government and the demand from customers. As shown by the Beta value of 0.016, the demand from customers and the need for automation had no impact on the factors of technology.

5.0 Summary, conclusion and recommendations

Organizational considerations, technological factors, and moderating factors all have a role in determining whether or not chatbot technology is used for real-time customer care help, as shown in the study. The variables that were examined were shown to have a correlational link with one another. There are nine main chatbot adoption variables that have been found based on the

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findings of data in this research. These considerations influence the prevalence of chatbots in telecom companies' customer care departments. These factors include:

- Perceived benefits: It's the perceived benefit of using a chatbot for real-time customer care help, such as saving money, improving the customer experience, and receiving assistance in real-time.

- Top management support: In order to turn policies into objectives, they need the backing of executives. They have a say on matters that impact the whole company. An invention is supported by them.

- Organizational readiness: It is the degree to which a company is ready to adopt novel ideas. Get equipped with the necessary information technology (IT) and monetary assets (financial and otherwise) to use chatbot technology.

- Compatibility: is the ability for two systems to function together as intended, with no modifications required. This is shown by the seamless integration of AI chatbots and human customer service personnel.

- Complexity: how easy or hard it is to use the system. In terms of simplicity of use, people are more likely to embrace a system that is straightforward and less likely to reject one that is convoluted.

- Technology availability/readiness: it is person's propensity to use new technologies for the purpose of improving their home life or their job. The new technology has to be trustworthy, safe, and backed by a solid infrastructure.

- Customer pressure: It's the demand from consumers who want answers quickly and often when they contact customer service for help. The need of automation arises from the fact that competing industries are incorporating new advancements into their day-to-day operations.

- Need for automation: A desire to automate certain operations on the part of the firm.

- Government regulation: The rules set up by the state about the way a business must carry out its operations.

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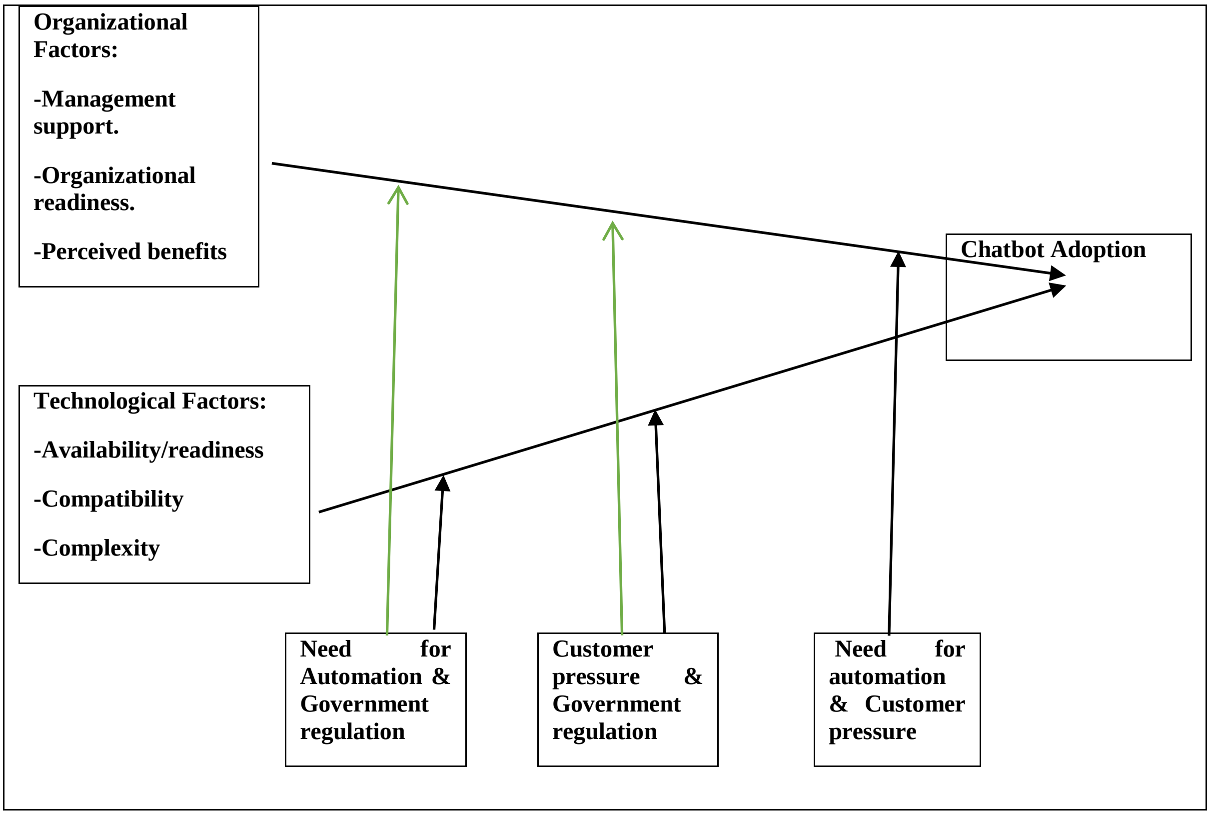

Fig. 2. Chatbot Adoption Framework

5. CONCLUSION

Technology that utilizes chatbots is applied in a haphazard manner and to a limited extent. Based on the results, it was determined that the telecommunications industry is prepared to embrace chatbot technology, particularly those that make use of open artificial intelligence and big language models, such as ChatGPT. As a consequence of automation, there will be a reduction in the number of human agents or customer-care representatives who are required, which according to the new technology will result in cost savings and improved consumer insights. A straightforward and suitable technology is required for the chatbot. The use of artificial intelligence chatbot technology has a number of benefits, including a decrease in the amount of time it takes to respond to requests made by clients and a reduction in costs. The adopted application must be a fair and responsible AI for consumers.

According to the findings of this research, the framework that was built has the potential to serve as a guiding principle in the process of implementing chatbot technology within the telecom business setting. As a consequence of the implementation of an artificial intelligence chatbot, users will not have to spend a large amount of time waiting for replies to their inquiries, which will ultimately lead to an improved customer experience.

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