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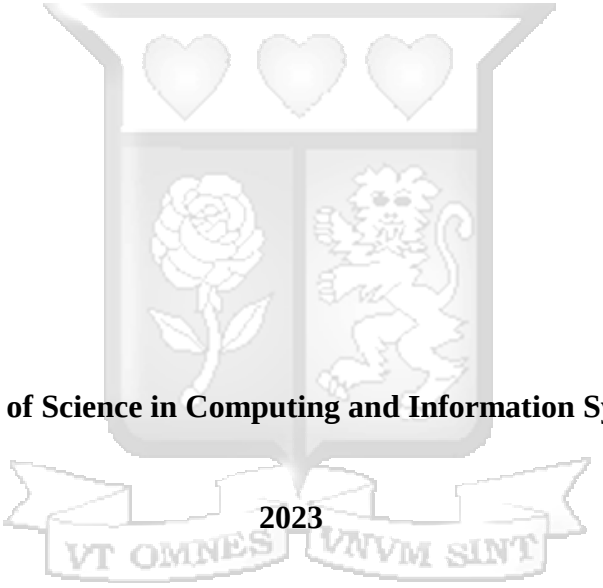

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Declaration/Approval

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

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Abstract

Harnessing knowledge in organizations is important in improving employee performance. Explicit knowledge is widely shared because of its descriptive nature and easy documentation. Tacit knowledge is under-utilized due to its intangible nature. It is knowledge based on experience embedded in a person. Tacit knowledge is gained from the continuous practice of organizational tasks, which helps build valuable experience, intuition, innovation, and better ways of handling situations. Experienced employees in an organization have more tacit knowledge compared to younger employees. When faced with a challenging situation at the workplace, younger employees need to consult experienced employees on the best way to tackle; if there is no one to consult they would have to try out their way or make mistakes and learn from them. When these older employees leave the organization they leave with a wealth of tacit knowledge embedded in them. Due to the lack of an efficient channel to share and store tacit knowledge, Kenya Railways loses loads of information that could help smoothen business processes save time and money, and improve the performance of its employees. Transfer of Tacit knowledge is crucial to Kenya Railways Nairobi Central Workshop because of the unique nature of its operations. To fill these gaps, this study explored the use of AI Voice detection to harness tacit knowledge. AI voice detection system was used to capture tacit knowledge in audio form and stored it in the knowledge base. Upon a user's request, the system base is queried to give the required feedback.

The development of the AI voice detection system adopted Agile Software Development Methodology. This methodology is an iterative and incremental approach to software development. The data collected targeted engineers and technicians in the Nairobi Central Workshop working on the repair of Locomotives and DMU. The data included sources of tacit knowledge, challenges in sharing it, areas that require the tacit knowledge, and users' functional requirements of the bot. From the challenges identified tacit knowledge was gathered and fed into the bot. This information was used to constantly train the model to increase its efficiency in delivering tacit knowledge to users without human intervention. The data collected was classified into three broad categories: Training set, Test set, and Validation set. The training used supervised learning where the bot learned from labeled datasets.

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List of Abbreviations

AD	Active Directory
AI	Artificial Intelligence
ASR	Automatic speech recognition
DM	Dialogue Manager
DMU	Diesel Multiple Unit
DP	Dialogue Policy
DST	Dialogue State Tracker
GPU	Graphical Processing Unit
gTTS	Google Text-to-Speech (TTS)
IDE	Integrated Development Environment
KR	Kenya Railways
ML	Machine Learning
NCR	Nairobi Commuter Rail
NLU	Natural Language Understanding
NPS	Naval Postgraduate School
ROI	Return on Investments
SST	Speech to Text
TPU	Tensor Processing Unit
TTS	Text to Speech
UI	User Interface
VAD	Voice Activity Detection

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Chapter 1: Introduction

1.1 Background to the Study

Knowledge has been described by the Oxford Dictionary as the theoretical or practical facts, information, and skills acquired through experience or education. Theoretical facts also referred to as knowing –that, are beliefs that are distinct from opinion by justification and can be expressed in a declarative sentence. For example "I know the sky is blue". Theoretical facts represent information that is acquired through formal education. Practical facts are referred to as the knowledge of how to do things gained through exercise in the performance of procedural tasks for example "I know how to drive a car". They are skills learned through experience (Kurczewska *et al.,* 2020).

There are two types of knowledge; explicit and tacit knowledge. Castaneda and Toulson (2020) described explicit knowledge as universal knowledge that can be documented, stored, and accessible. It exists in the form of formally organized data and can be shared with people. It is the "know-what''. Structured knowledge, such as that found in explicit knowledge, is simple to describe, record, store, and transfer electronically. It is formalized through the use of a symbol system. Manuals, processes, laws, patents, formulas, articles, and technical papers are a few examples of explicit knowledge. Indeed, due to the tangible nature of visually articulated explicit knowledge, it is especially easier for its manifestation and transmission.

Further Castaneda and Toulson (2020) described tacit knowledge as knowledge gained through an individual's experience. It is an individual's experience and skills learned over time that build up to form their insight, intuition, awareness, ideology, or judgment. Perumal et al., (2022) describe tacit knowledge as "deeply rooted in action, commitment, and involvement in a specific context.

Tacit knowledge is hardly documented since it arises from a person's experience. Gamble (2020) stated tacit knowledge is solely in the minds of individuals and is not established in any tangible format. Due to its subjective, informal, and personal nature and lack of documentation, it becomes challenging to share it among people. Such knowledge can therefore be accessed by conversing with the said people (Castaneda and Toulson, 2020). It becomes ingrained in a person as knowledge, experience, or competence. However, social connections and regular encounters between people in a particular context are ways by which experiences, ideas, expertise, and skills are acquired and personalized.

Employees of an organization create and learn knowledge while performing various tasks at their workplaces, most of which remain in their minds. From their day-to-day operations, they learn how to perform, observe the nature and culture of the organization, and make mistakes that help activate their instincts and intuition. They learn how to perform optimally and efficiently (Huie *et al., 2020).* When tacit knowledge is shared among employees it puts them in a better position to maximize operations and avoid mistakes that would cost the organization time and money. Huie et al, (2020) further added to an organization, sharing tacit knowledge gives it an upper hand in handling its operations.

Castaneda and Toulson (2020) posit that, organizations currently require instruments to enable the exchange of tacit knowledge. These tools can be ones that disseminate knowledge through ICT. They contend that real-time operation, interaction, and the ability to stimulate cooperation are all necessary for ICT to be effective at knowledge exchange. Additionally, earlier studies based on interviews suggested that socialization—defined as chatting with coworkers—is a useful strategy for disseminating tacit information. As a result, ICT-based tools may be useful for transferring tacit information when verbal communication is the only method of interaction.

Kenya Railways is the only organization offering railway transport in Kenya. Over the years it has undergone rehabilitation to improve railway transport in the country. As a way to facilitate train movement Kenya Railways has hugely invested in the Nairobi Central workshop. A facility whose primary mandate is to develop, repair, service and maintain Locomotive engines, DMUs, Wagons, and Carriages for both commuter and passenger trains. The facility has undertaken major works such as the rehabilitation of locomotives and overhaul maintenance of locomotives and DMUs.

To properly harness this tacit knowledge a voice bot will be used. A voice bot is a conversational system able to communicate with a human. It is capable of understanding, interpreting, and analyzing requests expressed by an individual and vocally responding to them in the form of natural language using voice recognition. When a user speaks, the system detects their voice using Voice Activity Detection and transforms it into text using an Automatic speech recognition system. These two components make up the speech text engine. The text is processed by analyzing it using an artificial intelligence engine. Based on the information stored on the bot it chooses the answer and synthesizes it orally using a text-to-speech engine.

1.2 Problem Statement

For inexperienced employees to access Kenya Railway operations information, they are required to get information from their more experienced colleagues through consultation. If there is no one to consult an employee is left to perform tasks from their knowledge which may lead to making mistakes due to a lack of proper know-how. This creates a hit-and-miss phenomenon leading to inefficiency and inconsistency that many organizations in dynamic situations can no longer afford (Andrews & Smits, 2019). Moreover, when experienced employees leave their organizations, they leave with a wealth of operation-specific knowledge gained. Obrenovic et al., (2020) assert that conveying tacit knowledge among employees has become a challenge because this knowledge is embedded in the person rather than in existing documents.

This study proposes the use of AI voice detection software to manage and share tacit knowledge. The tool will enable experienced employees to record their knowledge verbally. The audio will be stored in the knowledge base and accessed anytime a user requests. Tacit knowledge is based on experience and is often embedded in an employee's brain and can be considered personal knowledge. Such knowledge is better administered orally through conversations and other social interactions and using the technological device can improve its management. (Obrenovic, Jianguo, *et al*., 2020 and Msoffe et al., 2020. The proposed system will assist in the administration of tacit knowledge without necessarily depending on a human. After he/she leaves the organization the tacit knowledge will still be available and accessible from the bot's knowledge base. An employee who may need this information will be required to query the tool verbally; and based on the data in its knowledge base the bot will give feedback- tacit knowledge verbally.

1.3 Objectives

1.3.1 General Objective

This study aims to develop a tool to harness tacit knowledge to improve employee performance in Kenya Railways using AI voice detection.

1.3.2 Specific Objectives

i. To investigate the sources of tacit knowledge within Kenya Railways Nairobi Central Workshop.

ii. To investigate the causes of challenges faced in sharing tacit knowledge within Kenya Railways Nairobi Central Workshop

iii. To analyze tacit knowledge required at Kenya Railways Nairobi Central Workshop for training the AI Voice Bot.

iv. To develop a tool for harnessing tacit knowledge among employees in Kenya Railways Nairobi Central Workshop using voice detection.

v. To test the functionality of the developed prototype.

1.3.3 Research Questions

i. What are the sources of tacit knowledge within the Nairobi Central Workshop?

ii. How is tacit knowledge shared within Nairobi Central Workshop?

iii. What tacit knowledge is required within Nairobi Central Workshop?

iv. How to develop a tool that will harness tacit knowledge among employees in Nairobi Central Workshop?

v. How will the functionality of the tool be tested?

1.4 Justification

Tacit knowledge is critical for the success of an organization. Since it is based on experience it presents a more accurate manner of running processes that have already been tried and tested. Diverse skills, experience, and talents are crucial for bettering overall organizational performance (Obrenovic, Jianguo, et al. 2020). Knowledge gained in rail operations is particularly unique and engrained in an employee. When tacit knowledge is developed and maximized it can prove to be beneficial and significant to organizational success in various ways.

To begin with, it contributes to the attainment of greater return on investment for projects in which tacit knowledge is applied which indicates its contribution to corporate performance through increased profit margins. Secondly, when some aspects of innovative technology performance rely on tacit knowledge to coordinate actions and specify improvement procedures, it affects how well an organization performs. This could have significant effects on how tacit knowledge affects the corporation's high performance over the long term. In addition, tacit knowledge is also considered an invaluable resource due to its ability to provide valuable insights that are unavailable in explicit knowledge and are instead inspired by personal experience; which is useful in unique practical situations that require unique sets of responses (Huie *et al.,2020)*. Based on the aforementioned benefits harnessing tacit knowledge will enable NCR operations employees to improve performance, offer better services, and smoothen succession and training of employees, increase profit margins and ROI on innovative projects. This will in line improve the performance of the

Ministry of Transport and contribute to the overall aim of the government on service delivery to its citizens.

For an organization to effectively tap into the tacit knowledge, this knowledge needs to be effectively managed and shared. Since tacit knowledge is based on oral interactions with colleagues, an effective tool for sharing ought to administer the knowledge orally (Obrenovic, Jianguo, *et al*., 2020). Msoffe and Lwoga, (2020) suggested that businesses might employ audio and video tools more often to electronically communicate tacit knowledge. Workers' comprehension and assimilation of tacit information may be aided by interaction or socialization. It is advised to research the efficacy of various sharing tacit knowledge instruments, such as mobile phones. The capacities of people have been improved by this specific technology. A voice bot, which is good for emulating human conversation will be able to deliver tacit knowledge orally. Bots are designed to simulate human conversational patterns. It accepts data in voice form converts it to text for processing and relays the information/feedback in the form of voice. This, therefore means this tool will be able to capture and relay tacit knowledge in its oral raw form for effective delivery. Using a voice bot will emulate oral interaction without the need for the physical presence of the employee sharing the information. The bot will eliminate the issue of distance and time (Shihab et al., 2020). Employees seeking this knowledge will not need to physically meet with other employees but can access the valuable knowledge via a bot regardless of distance or time.

1.5 Scope and Limitation

1.5.1 Scope of Study

This study aims on addressing how to optimally utilize tacit knowledge. Recent studies and research will be used to find out the significance, challenges, and suggestions in sharing tacit knowledge. It will address sharing and transfer of knowledge in Kenya Railways, Business and Operations Department, which has the Operations division, a section that deals with the maintenance and repair of locomotives and DMU for NCR. Nairobi Commuter Rail (NCR) services is one of the key mandates for the corporation in service delivery. In NCR services, the study will explore knowledge in servicing and repair of locomotives and DMU at the Nairobi Central Workshop.

1.5.2 Limitations of Study

The study will only focus on sharing and transfer of tacit knowledge among KR employees at the Nairobi Central Workshop. Due to the large nature and size of Kenya Railways Operations, the study will focus on the section of service and repair of Locomotive engines and DMU for NCR.

Chapter 2: Literature Review

2.1 Introduction

This section explores a review of the literature on tacit knowledge in organizations. It identifies different principles that contribute to sharing tacit knowledge in organizations. In addition, it has explored various models used in developing AI voice detection systems for sharing information. The review will lay a foundation for empirical analysis to identify the limitations of existing models and research gaps. These will contribute to the development of the conceptual framework of the proposed model of AI voice detection software to harness tacit knowledge in organizations. The information from this section will provide additional value and reference in the research conducted and the development of a prototype to fill identified gaps.

2.2 Theoretical Review

2.2.1 Tacit Knowledge in Organizations

Knowledge is seen as a very valuable resource for organizations in today's fast-evolving world. It is a crucial element that influences an organization's capacity to maintain competitiveness in the business world. Researchers and practitioners are beginning to acknowledge the importance and difficulties of knowledge and knowledge-sharing in organizations (Huie et al.,2020).

According to Hadjimichael and Tsoukas (2019), tacit knowledge is the knowledge that we draw upon in action (e.g. driving, teaching, operating a machine, etc.), but is difficult to have consciousness of or express in language. Andrews and Smits (2019) that much of what we accomplish at work is collaborative with others. Opportunities for shared learning are presented by these impromptu and more structured collaborative interactions, frequently through which the tacit knowledge is shared. Such knowledge is by definition more subjective and context-based than explicit knowledge. When teams are working to solve complicated, difficult, and dynamic problems, tacit knowledge exchanges take place. Both strategically and operationally, the learning opportunities gain importance. It is further argued that knowledge must move along the continuum from tacit towards knowledge that eventually becomes knowledge independent of the person who created it in the first place (Hadjimichael and Tsoukas, 2019). In the effort of understanding tacit knowledge in organizations, Hadjimichael and Tsoukas, (2019) maintain that this applies to not only technical activities but also to administrative tasks in bureaucratic organizations as well as in the world of science.

The Nonakian idea of tacit knowledge serves as the foundation for several presumptions. First, there is a continuum between tacit and explicit knowledge, with some knowledge parts being more implicit than others. Second, as it exists within people, it is hypothesized that tacit knowledge is first subjective. In the end, conversion allows for the objectification of tacit knowledge through language and its dissemination among people. Tacit knowledge has been linked to organizational performance in numerous studies. It is claimed that similarly at the individual level, organizational/group level tacit knowledge improves team performance by fostering shared knowledge that is absorbed and adroitly made available to team members, however, the mechanism connecting the two is not clearly stated. Tacit expertise, according to researchers, adds to the distinctiveness of organizations, which in turn improves performance. When they begin with "a specific narrow-focused technology that is sufficiently distinct from the technical knowledge base of the parent business that is tacit," even corporate spin-offs were found to expand more. (Hadjimichael and Tsoukas 2019).

2.2.2 Sharing Tacit Knowledge in Organizations

Members of an organization who exchange ideas (skills, experience, and understanding) that are pertinent to the task, information, and proposals with researchers, decision-makers, and service providers are said to be exchanging knowledge. Sharing knowledge means disseminating information to advance an organization's overall mission. It can be defined as the transmission of all or part of one person's knowledge to another (Oliveira et al., (2022). For Hwang (2022) Knowledge sharing is the process by which previously held knowledge is now transferred into a format that may be comprehended, assimilated, and applied by other people. Hadjimichael & Tsoukas, (2019) imply that by combining and being verified by the knowledge of other people, conversion enables subjective information to become objective. Knowledge bridging takes place during knowledge transmission as opposed to knowledge conversion. Agents attempt to fill in their knowledge gaps through conversation in interactional environments by drawing on common tacit knowledge.

Tacit knowledge sharing in the workplace is “a set of individual behaviors involving sharing one’s work-related knowledge and expertise with other members within one’s organization. (Perumal et al., 2022). Hwang (2022) goes on to say that through face-to-face engagement, such as casual talks,

direct interaction, storytelling, mentorship, networking, or internships, approximately two-thirds of the knowledge acquired in a work context is transformed into tacit knowledge, leading to complicated tasks to assemble. To obtain this kind of knowledge, coworkers must communicate with one another. The value of human capital will rise through the sharing of tacit knowledge. Tacit knowledge should only be transferred when there has been considerable personal contact, ongoing communication, and mutual trust between the parties. When its owner or holder joins a network or community, tacit knowledge is shared. Hwang (2022) argues that among other things, we can use personal encounters, gatherings of coworkers who need help, and direct observation as examples. Alternatively, we might think of intranet and internet networks, e-mails, databases, videoconferences, and teleconferences.

The notion of social interactions has limited implications in the creation and sharing of tacit knowledge. Its creation requires socialization and particularly, the creation of tacit knowledge occurs through close social interactions and experience sharing. The intensity and efficiency of social interactions are determined by the level of social capital the interacting individuals or groups organizations possess (Ganguly et al., 2019). These authors also state that socialization, which they define as the "process of converting new tacit information through shared experiences in day-to-day social contact and can be primarily learned through direct experience," is the origin of knowledge. Therefore, formal events like conferences and training sessions can contribute to the transfer of tacit knowledge. However, informal conversations, social networking, and employee interactions are where the majority of tacit knowledge transfer happens. Additionally, the ability and willingness of people to share their knowledge (knowledge donation) and put what they learn to use are crucial for tacit knowledge sharing (knowledge collection).

Hadjimichael & Tsoukas, (2019) argue that sharing tacit knowledge is complex and time-consuming. It is beneficial to create environments that promote the transfer of knowledge. It has been suggested that knowledge transfer may be impacted at the organizational level by partnerships with or acquisitions of other businesses. The autonomy granted to the acquired firm in these agreements is a crucial element for knowledge transfer. Higher autonomy is granted when the acquisition is driven by the want to gain access to new knowledge, whereas lesser autonomy is granted when the acquisition is driven by the desire to strengthen one's position in the market. This is because corporate culture and systems are ingrained with knowledge. When access to new

knowledge is the driving force behind the acquisition, altering organizational structures and cultures may imperil the newly gained expertise. However, when the goal of the purchase is to improve market position, altering the organizational structure and culture of the acquired firm won't put the acquiring organization at risk of losing the necessary expertise because it already possesses it. Hwang, (2022) observes that numerous businesses make an effort to gather tacit knowledge to codify it into documents like procedures or manuals. The extensive contextual information in tacit knowledge makes this conversion challenging, expensive, and time-consuming. Because of this, the gathering, sharing, and dissemination of such knowledge are frequently constrained, particularly in the context of continuing interactions between knowledge-seekers and knowledge-owners. The organizational context and features that affect knowledge management methods at a corporation heavily influence how employees engage in the interactions.

2.2.3 Indicators of Tacit Knowledge Sharing

Tacit information sharing involves the element of cognitive time and effort, according to Perumal et al. (2022). A list of indications that can be used to verify the existence of tacit knowledge sharing in an organization was put together by Oliveira, M. J. S. P. and Pinheiro in 2021. The ability and willingness of individuals to share what they know and apply what they learn is essential for both formal and informal tacit knowledge transmission, according to Mustari et al. (2022). Therefore, it is crucial to comprehend the particular traits that motivate people to share their knowledge.

2.2.3.1 Time Management

Due to their slowness, the tasks involved in information dissemination may not be compatible with the speed of business. Despite this, tacit knowledge sharing still takes longer to complete than explicit knowledge sharing. (2021) Oliviera et al. As a result, workers' availability to share tacit knowledge inside the company is the first tacit knowledge-sharing indication, according to Mustari et al. (2022).

2.2.3.2 Common Language

The terminology and expressions used, which frequently take on their connotations depending on the organizational context in which they are used, must be widely understood by the parties in order for tacit knowledge transfer process to be effective and efficient to avoid communication breakdowns between the emitter and the receiver (Oliveira et al., 2021).

2.2.3.3 Mutual Trusts

The more trust there is among the people that make up an organization, the lower the risks and uncertainties associated with sharing tacit knowledge are. Relationship Network - One of the challenges in sharing tacit knowledge is a poor diagnostic of the tacit knowledge requirements that each component of the business must meet, as well as the quantity and quality of knowledge that must be acquired to satisfy these requirements (Oliveira et al., 2021).

According to Mustari et al. (2022), people grow more motivated to act in ways that are beneficial to others as their relationships deepen. Furthermore, the members of the organization are more likely to trust one another when the dangers and uncertainties associated with sharing tacit information are fewer. Mutual expectations as well as common social and cultural standards are necessary for developing a trusted network.

2.2.3.4 Hierarchy

Organizational structures that are bureaucratic and hierarchical impede communication, information sharing, and eventually the sharing of tacit knowledge. The exchange of experiences is discouraged as each element works to accomplish and improve its outcomes and incentives.

2.2.3.5 Recognition and Reward

Support might take the form of compliments, acknowledgement, performance reviews that include knowledge-sharing practices, or inspiring objectives. To encourage volunteers to offer their knowledge and experience, organizations should thank and appreciate them. Fostering formal and informal communication, putting knowledge into practice, rewarding participation in decision-making, and inspiring a positive movement (Mustari et al., 2022). Organizations should acknowledge and reward their elements, according to Oliveira et al. (2021), so that they are inspired to keep imparting their expertise. Sharing tacit information in other ways should be rewarded in the same way that sharing knowledge through formal schooling is.

2.2.3.6 Coaching and Mentoring

Since an organization's knowledge transfer strategy can be centered on people or the reuse of codified knowledge, these are considered to be the most suitable techniques for tacit knowledge sharing. If an organization prioritizes interaction between the individuals who make up its membership, the emphasis is on their dialogue and interaction because it is through personal contact that knowledge is transmitted (Oliveira et al., 2021).

According to Mustari et al. (2022), mentor programs and a mentoring approach allow for more direct knowledge transfer from senior workers and volunteers with experience. Most importantly, mentorship frequently takes place informally in non-profit organizations. More equitable distribution of mentoring opportunities and organizational guidance in the process of knowledge exchange is made possible by the organization, which can make it more effective.

2.2.4 A Tool to Harness Tacit Knowledge

Artificial intelligence (AI) is the ability to perform tasks usually associated with intelligent beings by a computer-controlled robot or a digital computer. AI uses the application of machine learning and deep learning (Ughulu, 2022). Artificial Intelligence has been explored in making systems and machines imitate human capability and intelligence. According to (Von, 2018) AI has domesticated our private life in speech-based assistants, smart cars, drones, and computer games. He further adds that AI is fundamental in the economic and organizational space that holds many theoretical challenges and opportunities for management scholars.

There has been an increase in the application of AI in organizations. According to (Von,2018) Some of the organizational tasks performed using AI are, selecting job applicants, financial transactions, diagnosing patients, scheduling complex logistics, suggesting therapy, and advising clients on financials. Ughulu (2022) points out that AI transforms the internal operations of the company, increases conversion, and reduces teams' workload. The potential capability of AI technology produces research opportunities. Von, (2022) suggests exploring these opportunities of computer-assisted systems for automated reasoning, knowledge repositories, image recognition, and image recognition and natural language processing. AI provides two broad types of task output to organizations. These are decisions that are conclusions reached from algorithmic deliberation based on the data available and solutions that are alternative courses of action to resolve a problem. Hadjimichael and Tsoukas (2019) claim that recent developments in Artificial Intelligence (AI) have made it possible for machines to carry out a variety of complex activities for which Tacit knowledge was first believed to be crucial. Observing the advancement of autonomous vehicles, robots, and intelligent information systems has made it clear that these systems and machines appear to be able to learn and adapt. Since a computer software can play a board game and learn through machine learning (i.e. to improve performance in the execution of a task by identifying

patterns in sample inputs). It's time to consider new ideas in response to the topic of whether and how tacit knowledge contributes to the intelligence of artifacts.

Further, according to Kambhampati, S. (2021), AI systems have shown reasoning ability, whether in expert systems or chess, long before they were able to display any proficiency in the other fundamental components of intelligence, such as perception. In a sense, artificial intelligence (AI) has progressed from teaching computers to perform activities for which we (humans) have explicit knowledge to teaching computers to learn to perform tasks for which we only have tacit knowledge. The World Wide Web, the Internet, and other labeled data sources have made it possible for machines to search for patterns when humans are not quite able to explicitly provide them with knowledge. This has contributed to the recent revolution in perceptual intelligence. Thanks in large part to the impressive achievements in perceptual intelligence—including learning to recognize voices, images, and simple language—and bringing the benefits of those advancements to everyone via their smartphones and personal digital accessories, artificial intelligence technology has recently captured the public's imagination. The majority of these developments did, in fact, result from "learning" methods, but it's crucial to realize that they happened in "tacit" fields of knowledge.

AI is now regarded as the most significant and disruptive new technology for major enterprises, according to Benbya et al. (2020). However, outside of technology startups, the technology is mostly absent from smaller businesses and is still in an early stage in large ones. Organizations use AI to accomplish a variety of goals, including streamlining operations, improving current goods and services, developing new goods and services, enhancing existing goods and services, and enhancing decision-making.

The many kinds of AI systems have been studied by Benbya et al. in 2020. One type separates AI systems according to the type of intelligence they exhibit. A third type is based on the function that the AI system performs, while a second type differentiates AI applications based on the kind of technology contained in the AI system. These are the several types:-

2.2.4.1 Based on Intelligence

Philosophical considerations of AI center on the idea of intelligent machines—machines that can learn and adapt and think like people. Artificial narrow intelligence, artificial general intelligence, and artificial super intelligence are the three main types of AI based on this idea.

2.2.4.2 Based on Technology

A second typology distinguishes between the technologies incorporated into AI systems, such as rule-based expert systems, robotics, and machine learning (including its subclasses of deep learning and reinforcement learning), natural language processing, and robotic process automation (still in broad use although not considered a state-of-the-art technology).

Table 2. 1: AI Technologies

Technology	Brief Description	Example Application
Machine learning • Reinforcement learning • Supervised learning • Unsupervised learning	Learns from experience Learns from a set of training data Detects patterns in data that aren't labeled and for which the result isn't known	Highly granular marketing analyses on big data
Deep Learning	A class of machine learning that learns without human supervision, drawing from data that is both labeled and unlabeled.	Image and voice recognition, self-driving cars
Neural Networks	Algorithms that endeavor to recognize underlying relationships in a set of data through a process that mimics the way the human brain operates.	Credit and loan application evaluation, weather prediction
Natural Language Processing	A computer program able to understand human language as it is written or spoken	Speech recognition, text analysis, translation, generation
Rule-based expert systems	A set of logical rules derives from human experts	Insurance underwriting, credit approval
Robotic process automation	Systems that automate structured digital tasks and interfaces	Credit card replacement, validating online credentials
Robots	Automatically operated machines that automate physical activity, manipulate and pick up objects	Factory and warehouse tasks

2.2.4.3 Based on Function

This distinction differentiates between four types of AI: conversational, biometric, algorithmic, and robotic.

Conversational AI - refers to the general ability of computers to comprehend natural human language and to respond to it. These systems employ both text- and voice-based technology, and their functionality, range, and degree of embodiment all vary significantly. Simple conversational AI is typically used to handle repetitive client queries, whereas smart conversational AI, which is made possible by machine learning and natural language processing, has the potential to handle more complex tasks that call for greater interaction, reasoning, prediction, and accuracy.

Biometric AI: Biometrics can be used to assess a person's physiological (fingerprints, hand geometry, retinas, iris, or face image) or behavioral traits (signature, voice, keystroke rhythms). AI-powered biometrics uses tools like facial recognition, speech recognition, and computer vision for identity, authentication, and security in computing devices, workplace security, and home security, among other applications. Biological markers like the face, voice, iris, or retina are also becoming more popular, and significant research is being done to examine their potential for widespread usage. While fingerprints have the longest history as an identification marker and are still used in many applications around the world, other biological markers like these are also becoming more popular.

Algorithmic AI: focuses on using machine learning (ML) algorithms, which are a set of clear instructions that a mechanical computer can carry out. Some machine learning (ML) algorithms, including speech recognition and picture classification, can be trained on structured data and are tailored to particular task domains. Other algorithms, in particular deep learning neural networks, can improve themselves through learning from vast amounts of labeled data and performing a variety of tasks like classification, prediction, and identification.

Robotic AI: For many years, physical robots have been employed in factory automation to carry out certain duties. Robotic systems have recently included AI, especially ML and NLP, more frequently, allowing robots to progress beyond automation and take on more difficult and high-level jobs. Robots having AI capabilities can perceive, understand, act, and learn in their surroundings. Robots can now successfully navigate their surroundings, recognize items around them, and aid people with a variety of tasks, such as robotic surgery, thanks to this.

2.2.5 Conversational Artificial Intelligence in Organizations

Through algorithmic simulation and mechanical processes, artificial intelligence (AI) plays a crucial part in the decision-making process. It saves us time and solves issues with the best possible decisions (Bhardwaj and others, 2020). Chatbots and other AI-based Conversational Agents are becoming more and more crucial in businesses (Lewandowski and associates, 2021). Conversational AI fails to live up to expectations and needs more study. Organizational adoption of text- and speech-based AI is still in its infancy and lags behind consumer usage. (Meyer von Wolff et al. 2019; Feng and Buxmann 2020; Corea et al. 2020).

Meyar von Wolff et al., (2019) further add conversational AI bears the potential to assist, solve, or automate tasks in work processes by retrieving and structuring information and providing employees with cognitive relief. This is done by identifying solution strategies, providing decision support, and vocational training through knowledge provision.

Less is known about adopting this new class of IS in existing organizational processes, governance structures, and work routines and how it differs from other AI-based and traditional IS adoptions. Similarly, no frameworks guide the organizational roll-out and continuous development of novel self-learning and self-communicating systems (Lewandowski et al., 2021).

An AI voice bot can easily provide navigation components, input control, or information components. Equally, the structure process can be built using question-and-answer dialogs to diagnose different situations and add and support decision-making. A voice AI bot can be fast, intuitive, and efficient to use (Power et al., 2019). Authors have called for research regarding the practice-oriented and company-focused adoption of conversational AI (Corea et al. 2020).

2.2.6 AI Voice Bot in Organizations

The application of AI speech bots for service delivery is examined by Klaus (2020). He observes that the demand for time-saving and heightened convenience mechanisms is what drives consumers today. The problem of not having enough time or mental resources to make the best decisions has been resolved. According to Hoy, we are surrounded by evidence, whether it be through stock market transactions or grocery purchasing decisions (2018). Personal assistant bots from these new service platforms, like Google Assistant, Alexa from Amazon, and Siri from Apple, have begun making their way into consumers' homes via smart speakers (Hoy, 2018). Jadczyk et al., (2021) further describe an AI voice bot as a software layer embedded in a standalone

smart speaker, such as Home Pod, Amazon Echo, Google Home, or smartphone, allowing for the interpretation of human speech.

The usage of AI speech bots in the medical industry during the Covid 19 outbreak is examined by Jadczyk, et al. in 2021. Voice assistants (VAs), sometimes known as "voice chatbots" or "conversational agents," are now capable of speaking communication interfaces with users because of cutting-edge developments in artificial intelligence (AI) and machine learning. Technically speaking, conversational agents are cloud-based services that convert speech to text and text to speech when a user invokes a wake word and a voice command. These process-automated bots can follow rules and make decisions much like a human healthcare expert (ie, digital patient triaging). Voice technology has already been tried out in a variety of settings to support routine clinical tasks. Its uses encompass the following:

1. Education- superior services utilizing a knowledge database to respond to frequently asked questions (eg, first aid instructions).
2. The streamlining of processes (eg, medication reminders, prescription refills, appointment scheduling, bedside assistants, and paperless documentation).
3. Support for patients using individualized, rule-based clinical instructions (eg, instructions to reduce carbohydrate intake among patients with diabetes mellitus).
4. The Food and Drug Administration [FDA] categorizes data collection services as medical device data systems. Examples of these services include the collection of patient-reported outcomes, biometric tracking, and identification of health status changes demonstrated by the collection of medical history or remote home monitoring.

Due to the Covid 19 epidemic, telemedicine services were quickly implemented because it was not possible to deliver healthcare consultations in person. Within a few weeks, the use of virtual care solutions multiplied up to ten times, allowing patients to get clinical treatment remotely. Most of them include simultaneous, real-time contact between patients and healthcare professionals. Due to its time and resource requirements, this method is ineffective when treating big patient groups. AI-powered medical bots were among the new digital technologies that had to be implemented right away due to the COVID-19 pandemic.

Bhardwaj et al. (2020) investigated the use of AI in human resources tasks and its advantages for workers. The hiring and onboarding procedures, employee experiences, process enhancement, and automated administrative duties are some of the first improvements HR professionals should

expect among the various AI applications in the human resources industry. AI can be employed in the recruitment process to benefit both the hiring organization and its staff. For instance, AI technology can simplify application procedures by creating forms that are simpler to complete, effectively lowering the number of applications that are abandoned. Processes like benefits administration, pre-screening, interview scheduling, and others can be automated by intelligent technologies. While each of these duties is crucial for the overall performance of a business, doing the tasks that are a part of these processes may be time-consuming. As a result, HR professionals frequently find that they have less time to support their team in having a greater effect. Through chatbots and other remote support tools, AI technology enables new enterprises to access human resources from anywhere at any time. This modification not only allows new hires to complete the onboarding process at their own pace but also lessens the administrative strain and typically promotes quicker integration.

Dominic et al. (2020) have talked about the benefits of conversational AI for bringing on and keeping Younger employees on a project. Numerous studies have been conducted on the integration of immigrants into projects. Scripts, pathways, and instances of developers successfully joining projects are reported in some of the research that concentrates on newcomers to OSS projects. Other scholars concentrate on comprehending and addressing the difficulties in integrating newcomers. In the OSS setting, retention is also seen to be a challenge even though joining the project is challenging. Mentorship is frequently used to assist newcomers. They presented a bot that facilitates newbies' initial interactions with the community while also connecting them with long-term community members. The bot would, in theory, be able to connect newcomers to human support and recommend open-source projects and issues from proposed projects that would be of interest (expert programmers that have had previous successful contributions to the same project). The linked work is initially covered in this essay. According to Dominic, et al. (2020), this kind of conversational bot would improve project contributor retention.

2019 saw research by Power et al. on the desire for conversational AI. The need for conversational decision counselors arose with the introduction of interactive computing systems in the 1970s, such as the Hewlett-Packard 2000 Access Time Share systems. With the advent of cloud-based, artificial intelligence development platforms, it is becoming increasingly possible to create conversational software and decision-advising bots. Bots can create conversations that include

questions and answers. Voice bots can be used in structured and semi-structured decision-making situations.

To better understand the design, development, and deployment of speech bots for usage by managers, customers, and clients, more exploratory design science research is required. The market for smart speech/voice-based technologies will reach $15.5 billion by 2029, predicts a fresh global market research report from analyst firm IDTechEx titled "Voice, Speech, Conversation-Based User Interfaces 2019-2029: Technologies, Players, Markets." Thanks to technologies like Alexa, Siri, Watson, and Google Assistant, software simulations of human speech are becoming more and more lifelike. Systems for interactive voice response ask and respond to queries. You can "command" your digital assistant to carry out specific tasks, conduct activities, and do other "things" by using these technologies.

Robotic chat, voice AI, chatbots, talk bots, interactive agents, or other artificial conversational entities are computer systems that converse with a person through text or spoken instructions and responses. For customer service or decision support, many companies and websites advertise and assess voice AI and chatbot software.

2.3 Empirical Review

2.3.1 Model of a Personal Assistant

Salunkhe et al., (2019) from Mahasharta, India described a model used to develop a Personal Assistant for users to understand the interview methodology of various organizations. The aim is to enable the personal assistant to give users insights regarding the interview procedures of different organizations. Their personal assistant is based on a conversational AI. The structure of the Personal Assistant model is as follows:-

2.3.1.1 The Framework

The straightforward stream of how a user can utilize the Personal Assistant –

To begin with, a user begins a conversation with the Personal Assistant. Secondly, the personal assistant requests their inquiry. The user asks inquiries to the Personal Assistant. Lastly, at last, get the answers from the Personal Assistant.

Figure 2. 1: Personal Assistant Framework

2.3.1.2 System Architecture

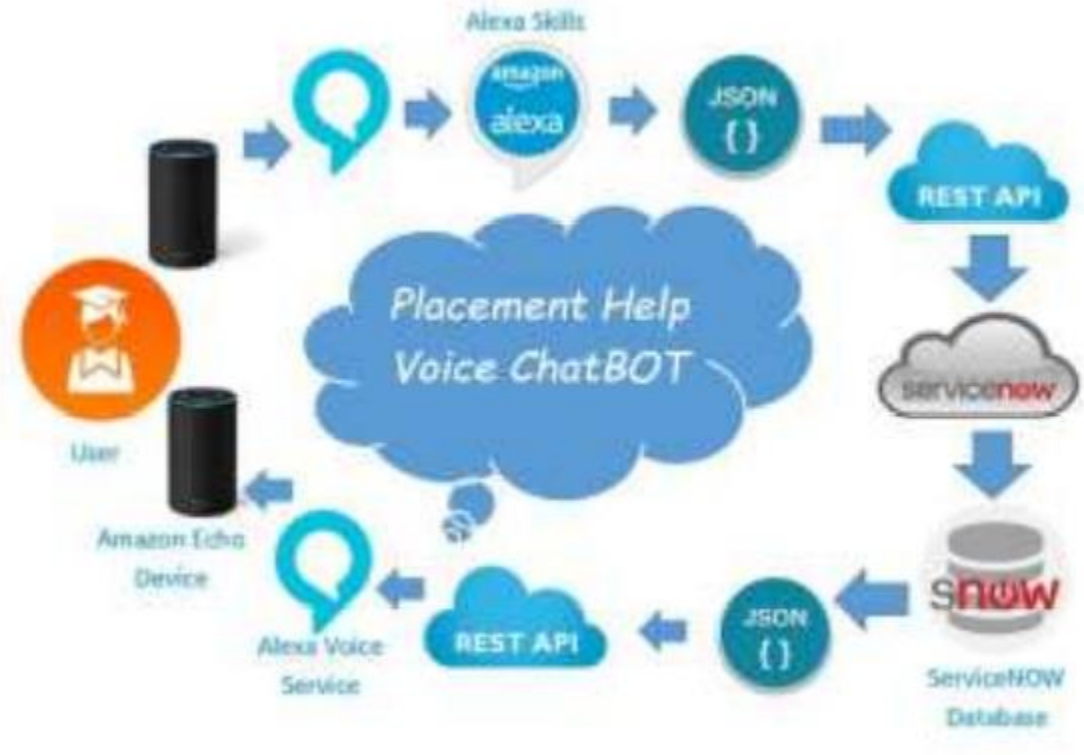

Figure 2. 2: Personal Assistant System Architecture

The Architecture consists of the end user, the echo device, and the voice service. The End User is a student or any fresh graduate looking for a job. He/She initiates the conversation with the personal assistant. Echo Device is a voice-controlled intelligent device. It takes the voice from the user and gives the voice response to Alexa Voice Service. Voice Service takes the voice from Alexa and converts it into text format. The architecture also has Alexa skills which combine the inquiries concerning the interview procedures. It gives the interview process details. JSON Response arranges the data from the user and being sent to the user as it gets it from Alexa Voice Service and vice versa. REST API is the affiliation point between ServiceNow and Alexa.

2.3.1.3 Process Flow

The Personal Assistant voice bot combines both the use of voice and text. The user inputs inquiry in voice, it is converted into text for processing and the output will be converted into voice then given to the user.

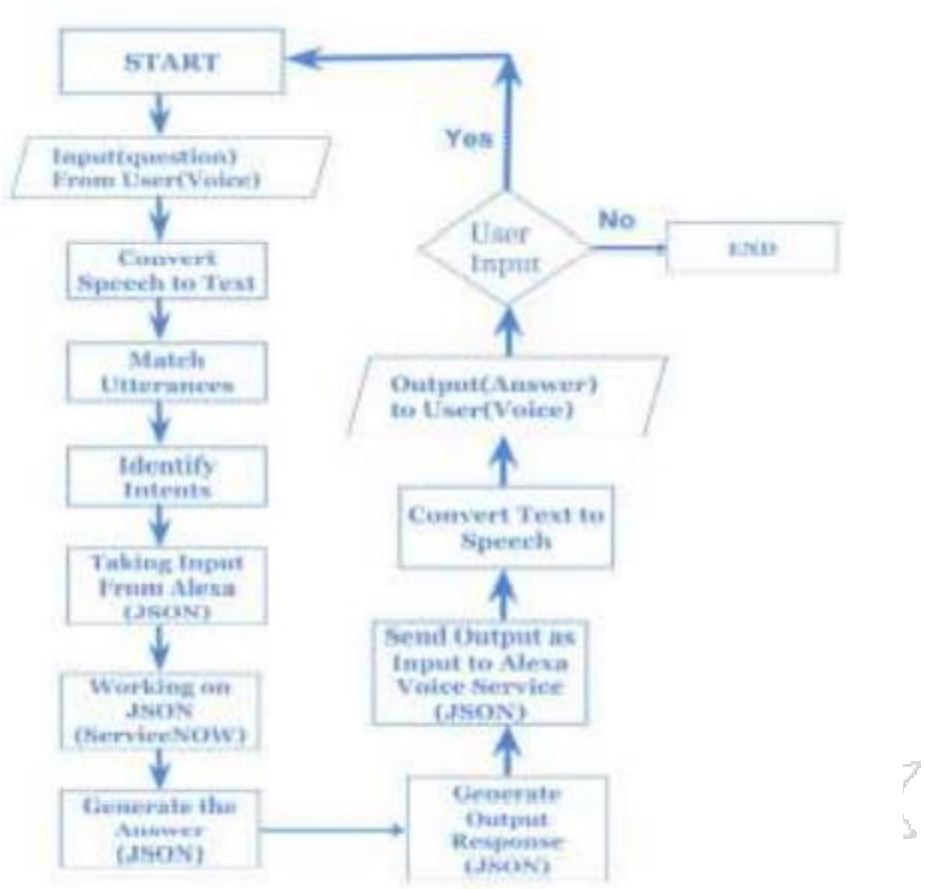

Figure 2. 3: Personal Assistant Process Flow

2.3.4.3 Algorithm

The suggested framework familiarized the Talk with Echo algorithm with the Alexa Voice Service. Talk with Echo, as the name suggests, is an Amazon Echo via which users may communicate with our Personal Assistant. The Talk with Echo algorithm consists of the following components:

i. Create Alexa Skills in Alexa Voice Service (Alexa Voice Service Side)
ii. Connect with Alexa Voice Service (Service Now developer side)
iii. Process and Generate AVS response (Service NOW Developer Side)

2.3.2 Model of a Travel-Based Voice Bot

Prof Khan et al., (2018) show the statistical model of a voice bot implementing artificial intelligence based on Artificial Intelligent Markup Language (AIML), speech recognition, and natural language processing. This voice bot is to be used by humans to book railway tickets using voice commands. The structure of the travel-based voice bot is as follows:-

2.3.2.1 System Architecture

The following figure gives information on the system architecture.

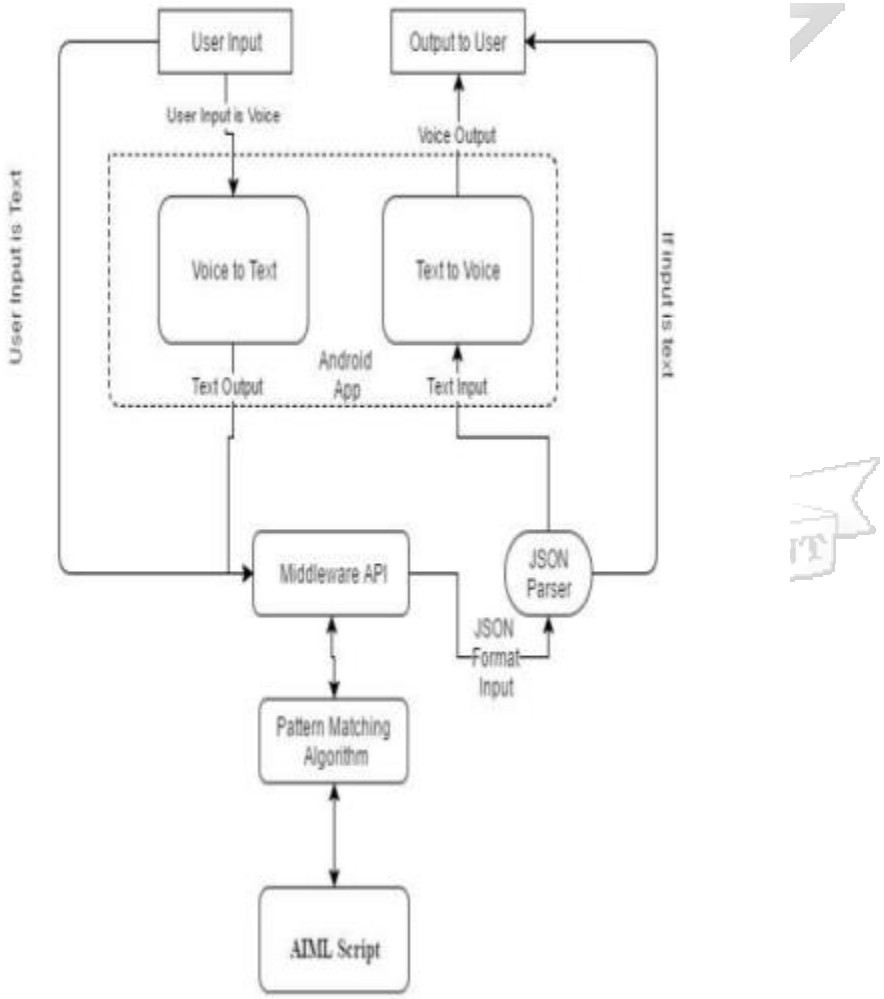

Figure 2. 4: Travel-Based Voice bot system architecture

The system operates in both text and voice modes. The user's input in text format activates the first mode. The middleware API receives the user input and returns a response. The second mode, however, is engaged when the user speaks, and in this case, the voice input is converted into text before being sent to the middleware API. The model that links the AIML scripts to our Android app is called middleware. The pattern matching algorithm processes the user input after receiving it at the middleware, which then runs the AIML scripts.

The pattern matching method is first used in this procedure to match the legitimate response from the available AIML scripts. The corresponding template is returned to the middleware when the pattern is matched. After that, middleware converts the template to JSON format and replies to the Android app. The program decodes the JSON and provides the user with the response after receiving the response. The response generation process is carried out in two phases:-

i. Pattern Matching Preparation - There are two primary stages that every input to the AIML interpreter goes through. Creating the input path for each sentence and normalizing the input.
ii. Pattern Matching Behavior: In this case, we try to match the input words one at a time to identify the largest and best matching pattern. This behavior can be explained by a master set of files and folders called the node master that contains a set of nodes, and branches that reflect the first words in all patterns.

2.3.3 Model Voice and Chat Bot Architecture

Baptista, (2022) from the University of Porto, Portugal in his study explored developing a system to automate communication flows of both voices and chat using Artificial Intelligence for IPBRICK. This will enable IPBRICK clients and partners to report technical issues directly to their services. Communication with the bot will be via speech and the bot will formulate an audible response that will be communicated to the user via speech.

Before designing the architecture of a voice-based bot, it is important to understand how the system works as a whole. This may be determined by looking at how it breaks down into a number of key components and how each one engages with the modules next to it. Input for this sort of communication is supplied verbally, typically through a microphone, and the assistant processes the request before responding audibly. Through a private telephone system created using the

Asterisk software, a user's UCoIP web page, or by dialing the matching SIP address in IPBRICK CAFE, users can make voice calls to one another using IPBRICK UCoIP.

This idea of two-person interaction was improved, taking into account Asterisk's extensive customizability, by creating a unique dial plan script tailored for human-to-bot conversation using the Rasa Bot Framework. Figure 2.5 illustrates a user-virtual assistant interaction using IPBRICK UCoIP in which the dial plan script is executed immediately upon a call request to the bot.

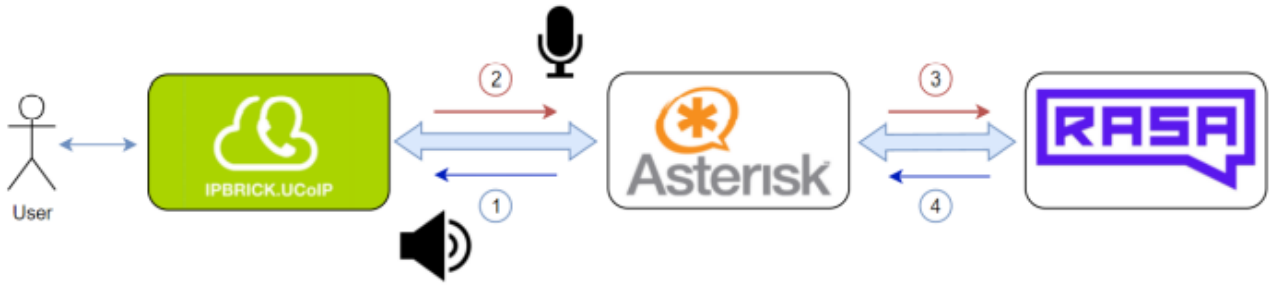

Figure 2. 5: Voice and Chat Bot framework

i. Starting out, Asterisk plays a message through an audio output. This establishes the initial environmental factors that the user will recognize.

ii. An audible notice is played after the user has heard the contextual message to let them know they can respond now. The vocal response is often recorded using a microphone and then processed by the Asterisk dial plan script.

iii. After starting a custom program, Asterisk sends the message to Rasa, who then uses it as input to execute the relevant response generation mechanism and come up with a suitable response.

iv. Rasa then generates a reply and transmits it to Asterisk, which then gets ready to play the message back to the user and ends the custom program before repeating step 1 with the most recent message. Until the user chooses to end the call, this cyclical process continues to run.

v. The user must be provided with context at the start of the call for them to reply appropriately. One of the options used to configure a virtual assistant in the IPBRICK OS

is the Dialogue start message, which turns any text entered into an auditory file and plays it at the beginning of a call. When a user calls the assistance, a fresh Rasa session is started and it waits for input from the user. Asterisk therefore plays the audio file again to the user at the beginning of each call to clear up any ambiguity in the user's initial speech. By providing the initial frame of reference, this prevents messages from becoming illogical.

Since the Rasa bot framework can only handle text as input, the problem is in reliably translating speech into text so that it can be processed by the assistant and translating Rasa responses into an audible format so that they can be played back to the user via an audio output. Speech-to-Text and Text-to-Speech engines are two more components in the aforementioned Asterisk custom application, system-bot.py, that are there to address this difficulty. Some of the Google Cloud Platform's cloud computing services, including the Google Cloud TTS and Google Cloud STT APIs, are utilized. They are crucial in the conversion of both text and sound. These engines contribute to the voice bot's general structure by enabling it to understand human speech and to depict human traits, such as personifying the voice and changing its language and gender.

The TTS engine is first utilized for configuring the dialogue message of the virtual assistant via the IPBRICK OS web interface, turning the inserted text into an audio file, using the same method as the voice bot in figure 2.5. This file is played through an audio output by the script at the beginning of Asterisk's dial plan. The STT engine in Asterisk's custom program then handles the audio file, translating it into a text-based format when the user offers an audible input that is saved in a file.

The same input format is used to enter this content into a JSON-type structure, which is then sent to Rasa for processing. Following the creation of a response, the information in these messages is transmitted to a TTS engine, which converts it into an audio file and saves it in a designated directory before terminating the custom application. The call plan script for Asterisk restarts and plays the just created file to the user. After that, all audio files are deleted, and a fresh round of dialogue starts. The voice bot architecture is provided in its entirety in the section below.

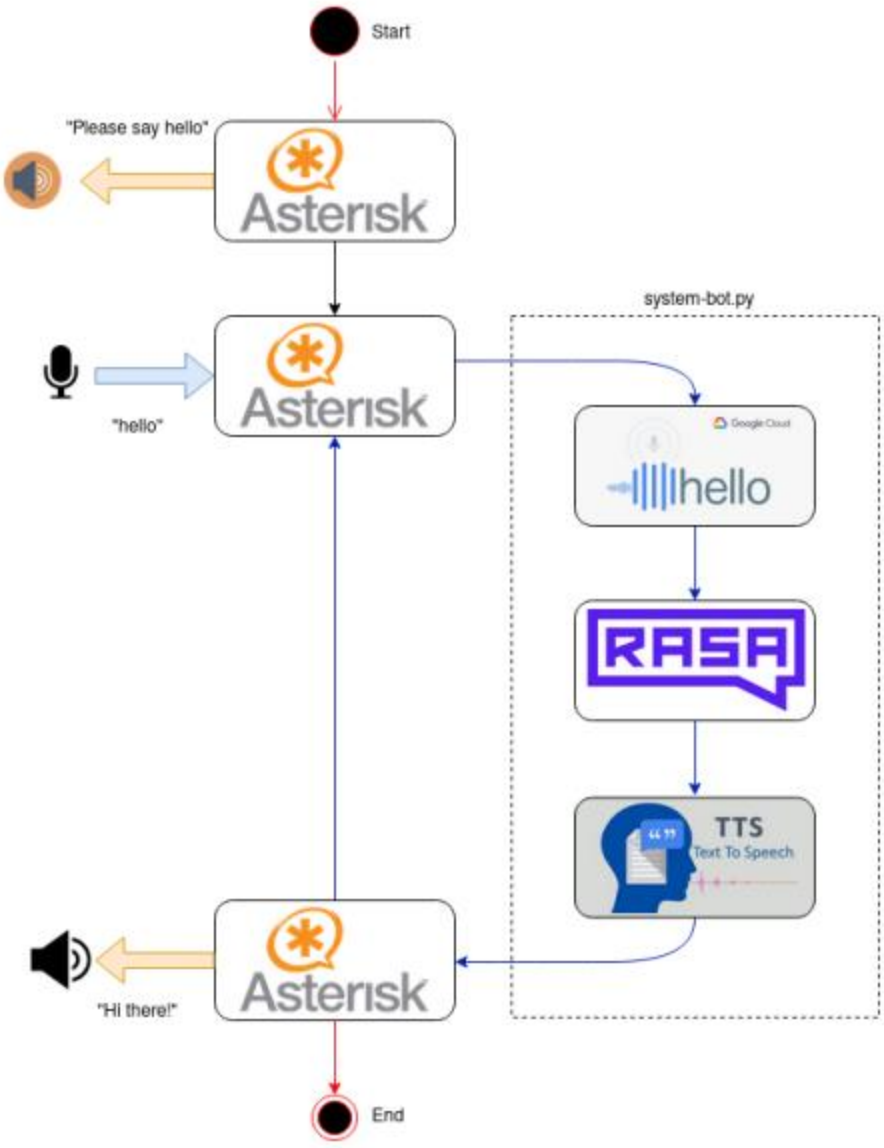

Figure 2. 6: Voice and Chat Bot System Architecture

A specific dial plan script is prepared for each virtual assistant created in the IPBRICK OS interface, containing a number of parameters pertaining to their internal parts and configurations. Some of these options specify the STT and TTS engines that are utilized, the assistant's language and gender, as well as the Rasa server port where messages are transmitted. The majority of this data is used in system-bot.py, even though it is first kept as a set of variables defined by Asterisk. The custom program has a generalized structure so that it may be utilized by any virtual assistant that already exists, along with their own configurations. Asterisk offers an interface between its

dial plan script and other programs, the Asterisk Gateway Interface, where these variables are called and adjusted, altering the direction of the communication channel as necessary, to successfully choose the proper parameters for a certain assistant.

2.3.4 Model of Voice-Based Email Application for Visually Impaired

Panchal et al., (2017) explored the development of a voice based email application to enable the visually impaired use and interact with email services. This application on converting will work on converting text to speech and vice versa to facilitate sending, reading or replying emails for the visually impaired.

Flow Diagram

i. STT: Accepts human speech and generates text.
ii. Language Understanding Component: uses a predefined language to extract semantics from a text string.
iii. Context Interpreter: By acquiring context information from a dialog history, the Language Understanding Module's semantics are improved. For instance, the Context Interpreter can replace a pronoun with the noun it refers to.
iv. Dialog Manager: Asks the user for input, interprets the response, and decides what to do next according on the directions in the provided dialog script.
v. Language Generator: takes text from the dialog manager and converts it into spoken voice for the user using a text-to-speech synthesizer (TTS).
vi. Text-to-Speech Synthesizer (TTS): accepts language-generated text and generates auditory signals that the user perceives as a human voice.

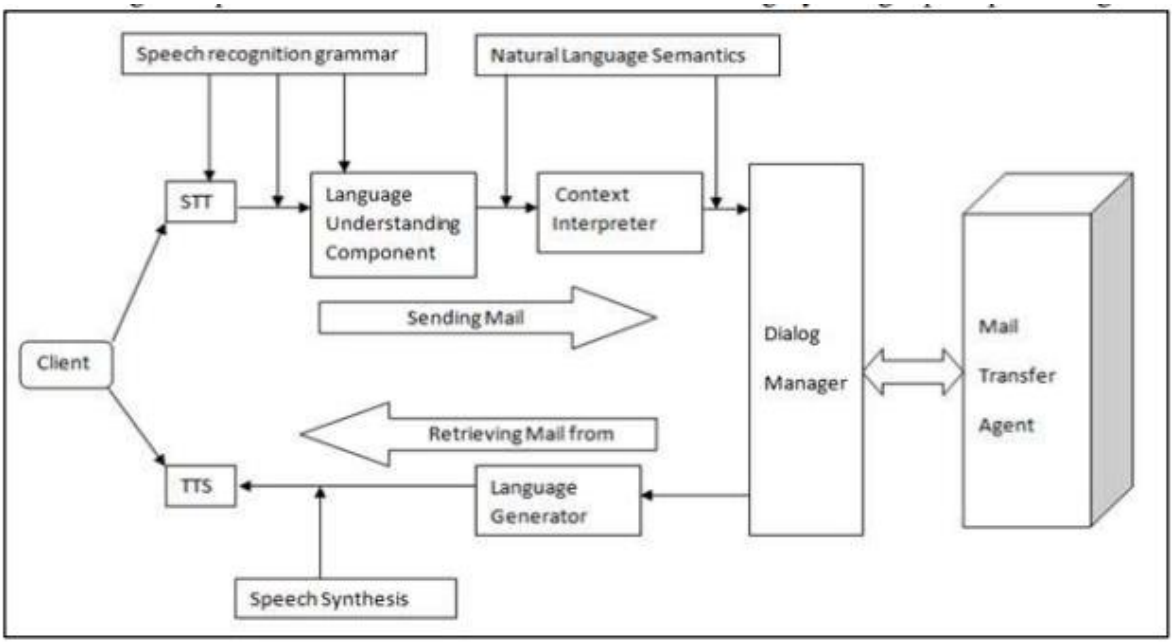

Figure 2. 7: Voice-Based Email Application Framework

The Modules of voice-based email application system are as follows:

i. Registration: The application's initial module is this one. The user must register in order to utilize our application. The application will ask for the details that must be entered in this module. As a result, the user will submit the information verbally. The system will invoke approval before submitting the details. Following registration, the database will retain all the data together with the username and password.

ii. Login: Once registered, the user can access the application by entering his or her username (email address) and password to access their account. It is possible to authenticate using this module. The username (email address) and password will be extracted in voice format and converted to text. The system will then use this text to determine whether or not the user is legitimate. The system will move that user to the following GUI if they are an authorized user. A successful login prompts the application to do some action, such as compose, Mail sent and received.

iii. Compose Mail: In this module, user can set up mail he/she wants to send. It works as follows:

a. The application will request for recipient's name/s, subject and message body.

b. User will supply this information through speech and this speech is transformed into text by the application. After that application will read recipient name, subject, and message body and ask for affirmation.

c. Once the affirmation is done mail will be sent to respective recipient/s.

iv. Receive mail: This choice enables a user to view all emails that have been delivered to his or her account. When this option is selected, the most recent emails are loaded. The recipient's name and the subject of each message will then be invoked by the program; if the user wants to listen to the mail, they must carry out the action stated by the invocation. He must use the proper voice command to go on to the next emails.

v. Sent Mail: The user's emails are tracked by this alternative. The user must carry with the instructions supplied by the invocation to move between emails in order to access the sent mails. This will make it easier for the user to quickly get and forward the needed mail.

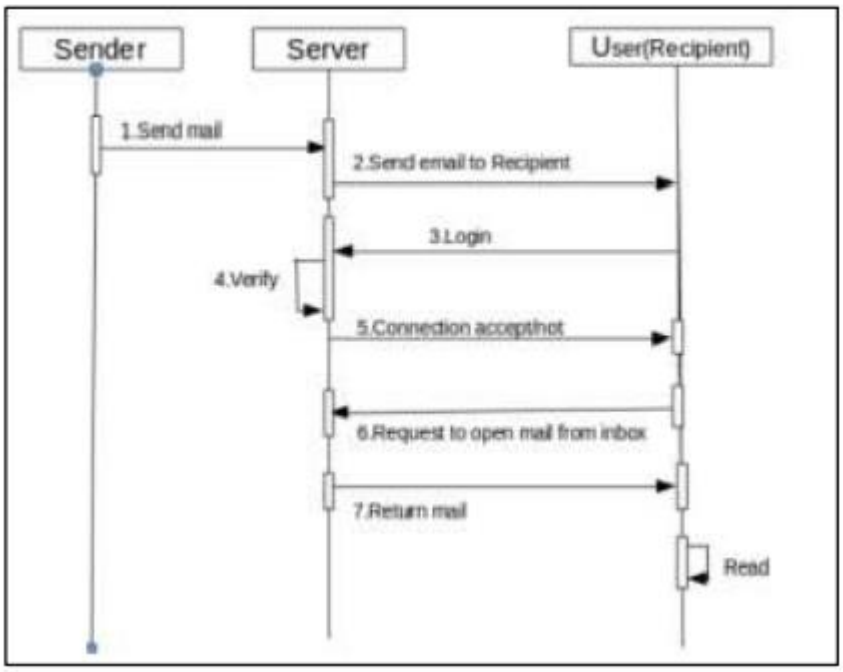

Figure 2. 8: Voice-Based Email Application Reading Sequence Diagram

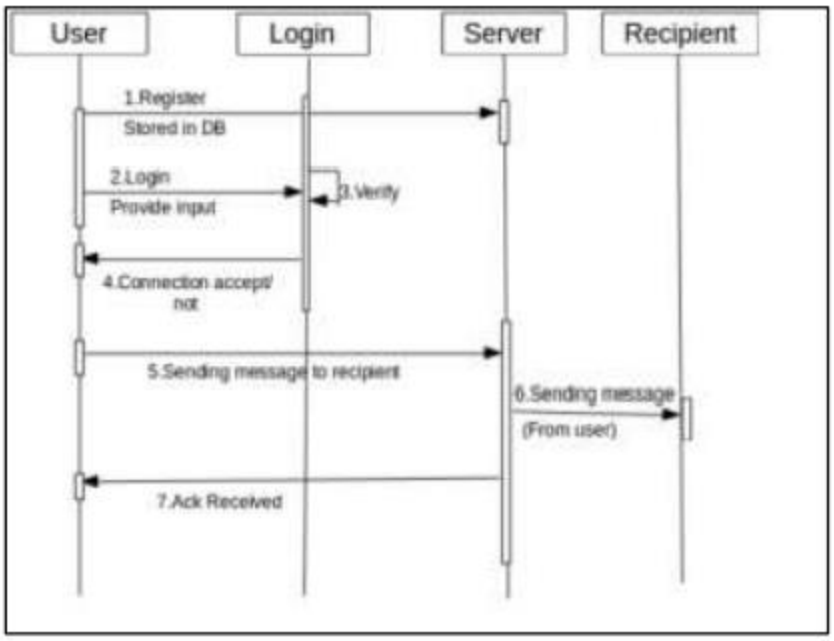

Figure 2. 9: Voice-Based Email Application Sending Sequence Diagram

2.4 Empirical Summary

Table 2. 2: Empirical Review Summary

RESEARCHER	MODEL	FEATURES	APPLICATION	LIMITATION
Salunkhe et al., (2019) from Mahasharta, India	Personal Assistant for user to understand Interview procedures	Alexa Voice service , Artificial Intelligence, Automatic Speech Recognition, Natural Language Understanding	The aim is to enable the personal assistant give a user/students insights regarding the interview procedures of different organizations.	The Personal assistant cannot get users sentiments from the user hence difficulty interpreting users intent and engage in a more natural conversation
Baptista, (2022) from university of porto, Portugal	Voice bot to enable clients and partners of IPBRICK report technical issued	Artificial Intelligence, Automatic Speech Recognition, Audio transcription,	This will enable IPBRICK clients and partners to engage with the bot to make report technical issues and get feedback via speech	For the bot to convert speech to text the spoken input was stored as an audio file and sent to the google platform to perform text conversion which lengthened the processing time
Panchal et al., (2017) from Goa College of Engineering, India	Voice Based Email Application for Visually Impaired	Android Studio, Automatic Speech Recognition, Natural Language Understanding	An android application, designed specifically for visually challenged people. It provides a voice-based mailing service to allow them to read and send mail on their own.	The application does not allow for further question-and-answer interactions by the user on using the application.

Prof Khan et al., (2018) College in Davangere, India	Artificial Intelligence based Travel Bot	Artificial Intelligent Markup Language, Speech Recognition, Natural Language processing	This voice bot is to be used by humans to book railway tickets using voice commands.	When a user poses a question to the bot it matches a reply from the AIML formulates a response. The bo does not interact further with the user to check the actual intent of the user.

2.5 Research Gap

The summery above shows limitation on the developed voice bots did not consider sentiments or seek clarification from the user to determine the best reaction to action. Also when encountered with unplanned responses from customers the voice bot to failed in giving responses since it does not know how to respond.

2.6 Conceptual Framework

The AI voice bot will be named Rail bot. Rail bot employs AI technologies such as Automatic Speech Recognitions, Natural Language Processing, and Dialogue Management. The components work together as follows:-

2.6.1 User Interface

This is the front end of the bot that provides the user with windows, icons, and menus for interacting with the voice bot. A chatbots user interface (UI) consists of a number of graphical and linguistic components that enable communication between humans and computers (Baptista, 2022).The user's interactions with the bot, including the introduction of all inputs and the receipt of all responses, will be displayed. Rail bot will be accessed via web of which the web continues to be the world's largest digital surface

2.6.2 Automatic Speech Recognition

This engine enabled human-machine communication. It is made up of a speech recognition component and voice activity detection. It uses AI algorithms to convert speech input into text, allowing Rail bot to understand the users input its aim is to derive what is being spoken. Using the VAD cancels out noise from the audio input and the STT accurately converts the spoken input into text for processing (Dong, 2016).

2.6.3 Natural Language Processing

This engine is used to derive understanding from user input that can be used to give relevant responses (Li, 2018). It uses AI techniques to analyze and interpret input extract meaning from a conversation. It uses algorithms that use human text as input to interpret and derive correct entities, meaning, and intent to the extent to be able to give useful text output (Baptista, 2022). The intent is the action/verb that the user wants to perform when talking to Rail bot whereas an entity is a keyword/noun used to describe the user’s request. NLP uses a Natural Language Understanding module which by extracting entities and intent interprets human language by representing useful

data into a valid form that can be processed by the dialogue manager. The NLU will resolve meaning from a user's input by checking the grammar and syntax, checking the meaning, and understanding the context. For example, in this system intents would include writing a memo, creating a schedule, creating terms of reference, or booking a meeting. Entities would include departments, time, date, Job titles, amount, place of destination, or place of departure. Dialogue acts are also derived at this point which are hidden actions in a user's input which would include making a statement, giving an answer, or asking a question.

2.6.4 Dialogue Manager

This module holds entities and intents to provide the relevant flow of the conversation or formulating answers. It controls the conversation by deciding the next action in the context of the ongoing conversation. It can prompt the user for more input, and seek clarification of previous input or output results. It can keep records of the interaction within a single conversation to change its responses when necessary (Baptista, 2022). The output of DM is in form of instructions sent to the NLG to make it in a human-understandable form for output. The dialogue manager comprises two main parts Dialogue State Tracking and Dialogue Policy.

2.6.4.1 Dialogue State Tracking

Is responsible for taking in information from the NLU and mapping it into a required dialogue state as per the state space. The state space contains all the information required to make a response or decision. By mapping, it identifies whether the information provided is enough to make a response. For the DST to maintain a dialogue state it may use the information entered by the use or exploit the conversation context (Brabra et al., 2021).

2.6.4.2 Dialog Policy

It is responsible for deciding the next step based on the dialogue state. According to Brabra et al., 2021, the dialog policy maps the Dialogue State into the most appropriate action represented as a dialogue act. These actions are found in the action space, the action may include Requesting, Clarify, Paraphrase, Informing, Setting the date, Executing. The dialogue state are:-

Types of Dialogue

The types of dialogue a DM will engage in include

i. Standard – This is when Rail bot has recognized the users' input through the intent it triggers the standard dialogue.

ii. Fallback – This is when Rail bot is unable to recognize the users' input through the intents it triggers the fallback dialogue.

iii. Disambiguation – This is when Rail bot has recognized the users' input through multiple intents and thus seeks clarification from the consumer by triggering the disambiguation dialogue. This will also be a default dialogue anytime the standard dialogue is triggered.

iv. Auto Escalation – This is when Rail bot is unable to recognize a user intent after several attempts it triggers the Auto Escalation Dialogue. This dialogue frees the user from continuous back and forth. It will then offer the user an alternative to let it get response from the support team. The failed conversation will be sent to the developer/support so that they can update the knowledge base with the required response.

v. Survey**:** This is when Rail bot wants to find out the user's satisfaction level or experience. At the end of a conversation, the survey is triggered to gauge the users' satisfaction level. This feedback will be used to train and award the bot.

2.6.4.3 Knowledge Base

It records specialist human knowledge to aid in problem-solving. As a result, Rail Bot will be able to respond to user inquiries and deliver pertinent content. (Adamopoulou, & Moussiades, 2020).

The figure 2:10 is an illustration of the AI Voice Bot illustrates how the different components work together. The figure 2.11 illustrate a sample conversation showing the various type of dialogue that might be experienced while using Rail bot.

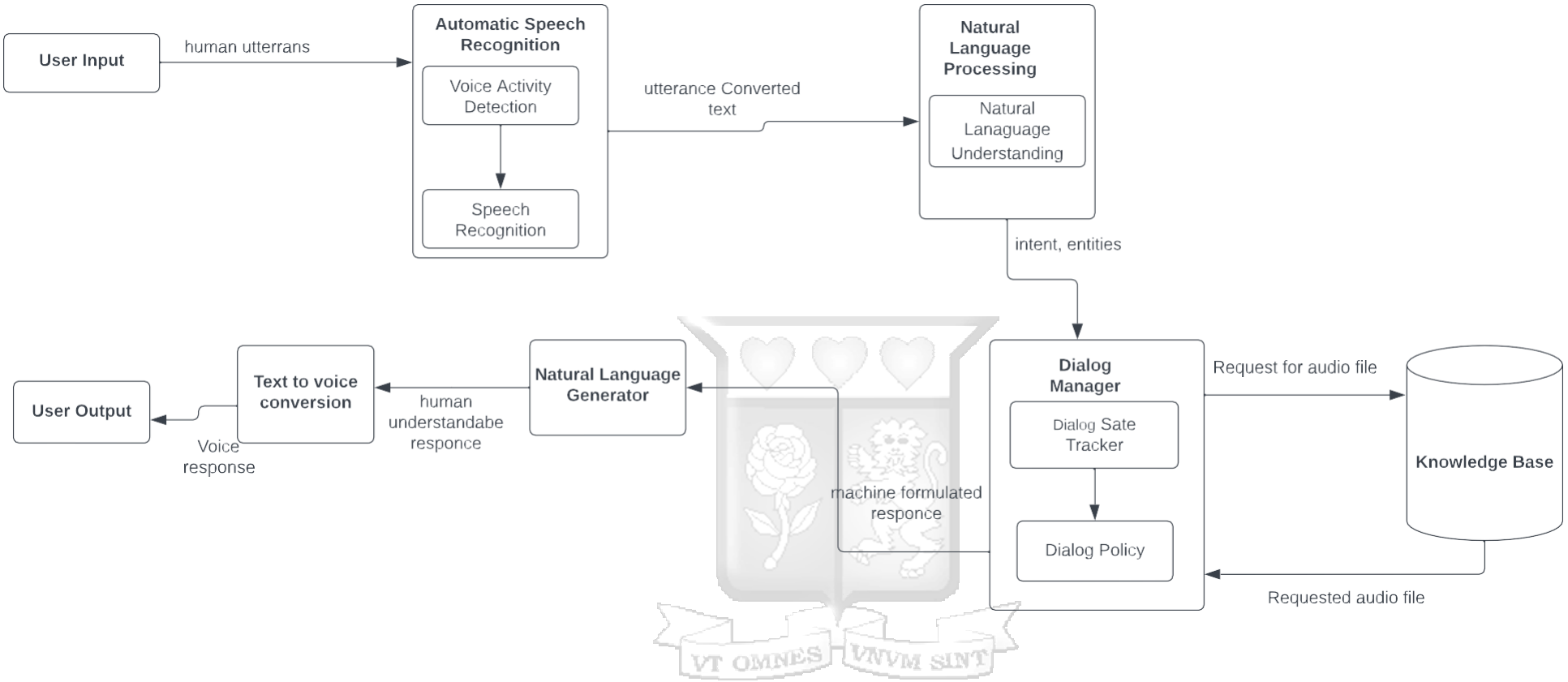

Figure 2. 10: AI Voice Detection Framework

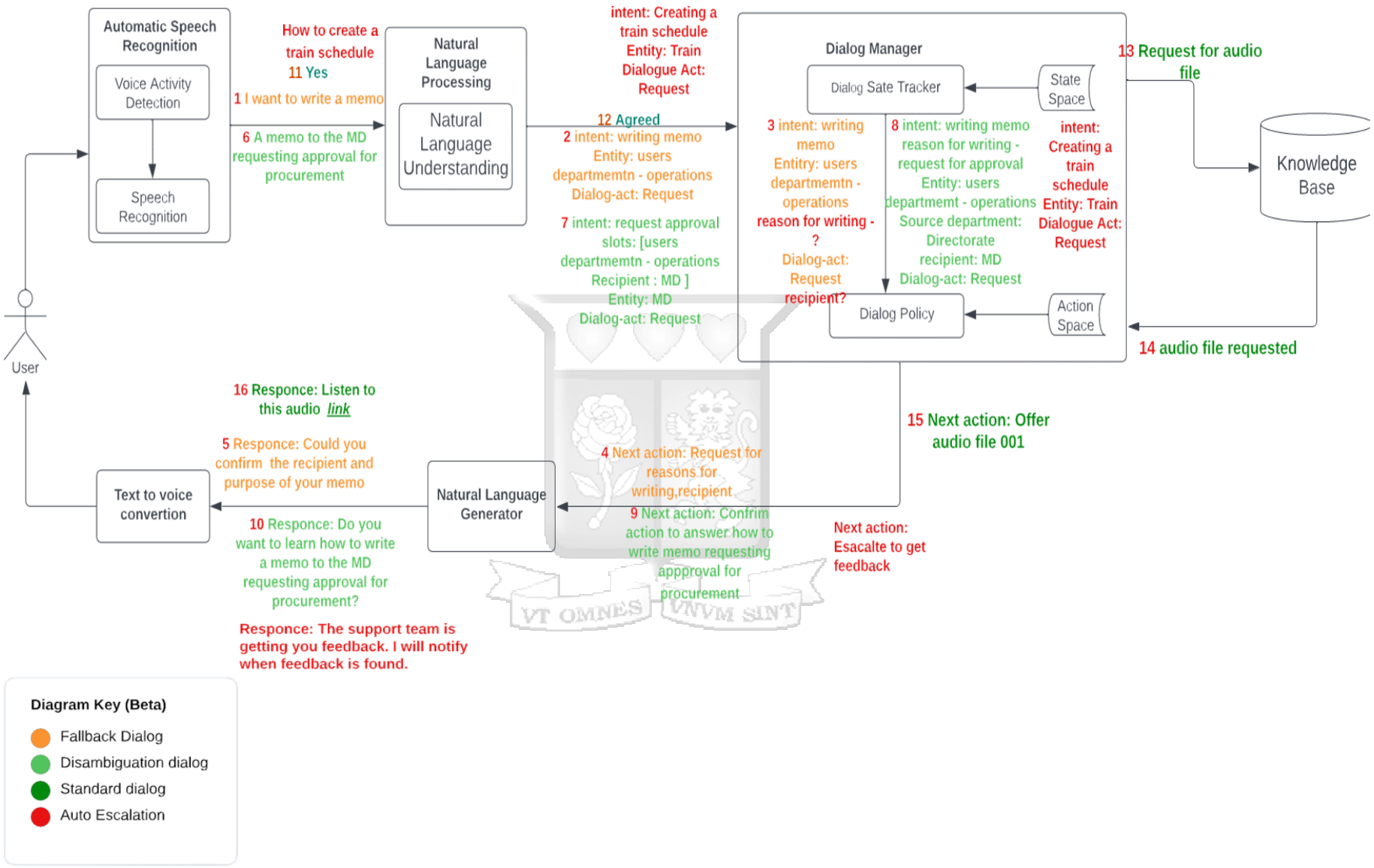

Figure 2. 11: AI Voice Detection conversation flow

2.7 Operationalization of Variables

The dependent and independent variables, as well as their connection, are the main variables that will be used. Sharing of tacit knowledge serves as the study's independent variable. In order to see how it affects the dependent variable, employee performance, this variable can be controlled and changed. In the relationship under investigation, it is the presumptive cause. The variable being measured and observed in response to changes in the independent variable is known as the dependent variable. It is the assumed outcome of the relationship under investigation. In contrast to the dependent variable, which is the result, the independent variable is the cause. The dependent variable is measured to observe how it reacts to the changes while the independent variable is changed by the researcher.

A unique measurement of tacit knowledge and a specific measure of employee performance must be identified in order to operationalize tacit knowledge as an independent variable and employee performance as a dependent variable in KR operations. A questionnaire and interviews will be used to gauge how well employees are able to assess the level of skill and experience of their coworkers as well as how effectively and frequently tacit knowledge is shared to solve problems. Based on the goals and objectives of the organization, appropriate metrics might be found for the dependent variable, employee performance. When applying tacit knowledge, performance can be assessed in terms of productivity and job quality (Ganguly et al., 2019)

Chapter 3: Research Methodology

3.1 Introduction

This chapter describes a systematic investigation that was carried out to study existing problems and build a foundation to the most suitable solution. This research sought out more information and knowledge in sharing tacit knowledge within organizations. The research comprises defining and redefining the problems, collection, organization, and evaluation of data in order to make conclusions and informed decisions. It involved all techniques, procedures, and methods used in undertaking research.

3.2 Application Development Methodology

The development of the proposed system adopted the Agile Software Development Methodology. This methodology is an iterative and incremental approach to software development. It breaks down the development process into smaller models that can be worked on in collaboration with the users. Agile methodology is considered appropriate for bot development (Power et al., 2019). This approach allowed the process to be flexible and adopt changes without the risk of redoing the whole development process (Al-Saqqa et al., 2020).

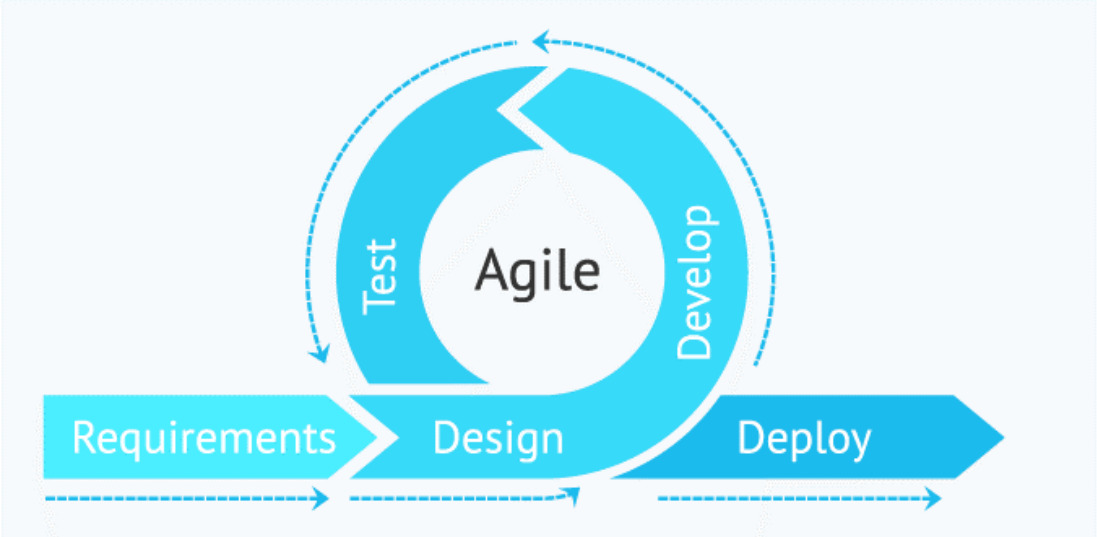

Figure 3. 1: Agile Software Development

The Rail bot will be a web based application.

3.3 Research Design

The research design involved a structural framework that was used to answer the research questions and achieve the research objectives. The research design enabled the research to pursue a defined direction in collecting and analyzing data. The outcome was used as a foundation for developing an AI voice detection system to harness tacit knowledge within an organization.

The dissemination of tacit knowledge has depended on face-to-face interactions between co-workers (Hwang 2022). This leads to a high dependency on the physical presence of the one sharing the knowledge which is not always guaranteed in a working setup. This problem leads to poor sharing and storage of tacit knowledge. The nature of this study which is based on the nature of tacit knowledge and the AI voice bot used to harness it; led to the use of a mixed approach in research. This study adopted mixed methods which combines elements of qualitative and quantitative designs.

Quantitative research involves collecting and analyzing numerical data. It was objective, structured, and measurable, and allowed for quantification of relationships. It was used to get responses on who is frequently consulted and what respondents would want changed. This assisted in building a foundation on who to interview as far as tacit knowledge is concerned. This research used questionnaires.

Qualitative research involved collecting and analyzing descriptive data which was in form of audio. This method assisted in answering questions like how and why which are the key questions when looking for tacit knowledge. It created insights into experiences. This improved understanding of concepts, facts, opinions, and experiences within Nairobi Central Workshop. This method aimed to explore tacit knowledge in the workshop. This research used Interviews.

3.4 System Design

This stage involved the components, architecture, and interfaces required to develop the system and to achieve its main objective. The system requirements were classified into hardware and software.

3.4.1 Hardware

These are the peripheral devices that were required for the system's functionality.

i. A computerized device

A computerized gadget will be able to reach Rail bot through the internet. A desktop computer, a laptop, or a personal digital assistant can be the device. The device must also be internet-capable because it will act as a physical intermediary between the user and the bot. It can be used by the user to provide input, or the bot can utilize it to take action. A website will be used to access Rail Bot (Baptista, 2022).

ii. Microphone and Speaker

For this kind of bot communication, a request is made orally, typically through a microphone, and the assistant processes it before responding orally. Rail Bot will accept user input (questions) and voice-deliver output (answers to the questions). A microphone will therefore be needed to record input and a speaker to provide output to the user (Baptista, 2022).

3.4.2 Software

i. Python Programming Language

Development of the system employed Python Programming Language. Python was applied in deep and machine learning. This was because of its simplicity in syntax and multiple data science libraries such as Natural Language Toolkit (NLTK). In addition most deep learning frameworks are either built on python or adopt python interface giving it high performance (Brownlee, 2017 and Kamath et al., 2019).

ii. Naïve Baiyes

This was used in the training of the bot using the available datasets. Naive Bayes is a machine learning algorithm that is well-suited for classification in voice recognition. Naive Bayes will be used to categorize audio input into distinct groups when training a voice bot based on the probability that particular words or phrases will be present in the audio (Kamath et al., 2019).

iii. PHP

Web development was done using PHP language. This is because it is an open-source, easy to use with a large community of developers. It is also versatile and flexible (Kamath et al., 2019).

iv. Laravel

This is a PHP web application framework that is open-source and free. The extensive collection of tools and capabilities offered by Laravel make it simple to create scalable and maintainable web apps (Brownlee, 2017).

v. Flask

Flask will be used for building the APIs in Python because it provides a lightweight and flexible frameworks. It also provides built-in support for handling JSON data, which is the most common format used for exchanging data between applications.

vi. Google Colaboratory

The development will be done on Google Colab; a cloud-based IDE for creating machine learning models using python. Since it is hosted on the cloud it will enable easy access to needed resources such as GPU and TPU, and needed libraries. Since the functionality of the bot strongly depends on the host's computing capacity, its performance may differ depending on the Visual (Baptista, 2022).

vii. Studio Code

Visual Studio Code will be used as a support IDE for the User Interface. It is an IDE that supports debugging and task running. It also has a user friendly interface (Brownlee, 2017).

3.5 Target Population

The study targeted employees working in Kenya Railways, Business and Operations Department, which has the Operations division, in the section that deals with repair of locomotive and DMU for NCR. Kenya Railways Corporation is a State Corporation in the Ministry of Transport, Infrastructure, and Housing and Urban Development. The entire railway system in Kenya consists of a single-track main line from Mombasa to Malaba. The core mandates of the corporation are to provide efficient and effective rail services and inland waterways transport. Among its services are passenger services and freight. Kenya Railways has evolved and grown from the time of its inception. To support passenger services there exists Nairobi central workshop. The facility has undergone rehabilitation works so as to support and facilitate the maintenance of locomotives and DMU's. The facility has undertaken major works such as rehabilitation of locomotives and overhaul maintenance (https://krc.co.ke/the-nairobi-commuter rail/).

Throughout this development, KR has worked with employees who have gained knowledge in the rail industry. Given the unique nature of the rail operations, getting tacit knowledge on how operations are run will be useful to employees joining the department to learn how operations are done and handling of rail-specific challenges. The study will use a census which entails a complete enumeration and study of everyone in the Maintenance and repair of locomotive and DMU at the central workshop. The study targeted three senior engineers, two Mechanical and Electrical Engineers, one Locomotive coordinators, one assistant locomotive coordinator two Mechanical and electrical supervisors and twenty Mechanical and Electrical engine technicians. This is a total of 29 respondents in the Nairobi Central Station. In this research the target staff were categorized into strategic level (most senior), tactical level (middle level) and operational level (most junior). According to operation hierarchy in the Nairobi Central Workshop staff in the strategic level are senior engineers, tactical level are the Mechanical, Electrical engineers, locomotive coordinator and assistant locomotive coordinator and Operational level are the Mechanical and electrical supervisors, Mechanical and Electrical engine technicians. The interview targeted one expert engineer and two technicians to shed more light on tacit knowledge required in the day to day operations.

The data collected was categorized according to the objectives of the research. This included sources of tacit knowledge, causes of challenges in sharing tacit knowledge, tacit knowledge required and functional requirements of the bot.

3.6 Research Quality: Validity and Reliability

Upholding Research validity and reliability will ensure that the data collected is sound, replicable, and accuracy of results. This will contribute to the efficiency of the system. The reliability of the research study will be evident when the results among the respondents represent true and similar findings among similar respondents. The validity will be measured by comparing findings to other relevant sources, data, or theories. To ensure research quality the research will be planned in detail and adequate control measures put into place. This research will also consider a broad inclusion of respondents within the scope to enable verification through the comparison of findings (Patino et al., 2018).

3.7 Dissemination and Utilization of data

The data collected was categorized according to the objectives of the research. This includes sources of tacit knowledge, causes of challenges in sharing tacit knowledge, tacit knowledge required and functional requirements of the bot. Questionnaires collected data in sources of tacit knowledge and causes of challenges in sharing tacit knowledge. It will identify frequently asked questions, commonly used industrial terms and areas that require more tacit knowledge. Additionally the data collected helped in identifying from whom to get tacit knowledge. The information was used as guidance on getting relevant tacit knowledge from recommended sources and share the knowledge in the most effective way. This assisted in building up training data and performance of the Rail bot.

Interviews collected data in tacit knowledge required and functional requirements of the bot. This method helped in answering questions like how and why which are the key questions when looking for tacit knowledge. It created insights into employee attitudes, behavior, and experiences. This improved understanding of concepts, facts, opinions, and experiences within the organization. In addition, it was used in concentrating on different sections of the organizations with unique operations. This method aimed to explore tacit knowledge in organizations and understand how to develop a system that will harness the tacit knowledge. This section looks at what tacit knowledge is required for successful repair of Locomotives and DMUs. This data was useful in identifying areas employees need guidance from experienced colleagues. This enabled the system be developed to be user friendly and easy to use. In addition data collected on user requirements of specific functions guided on the development of the voice bot to meet the needs and support of rail operations.

The data collected was solely used for the completion of the dissertation project. This involved sharing the findings and insights gained from the research through the dissertation document. This equally enriched the research and contributed to the wider knowledge base on the relevant fields.

3.8 Risk Benefit analysis

For this study, a risk-benefit analysis is crucial. This kind of study entails weighing the project's prospective risks and rewards to decide whether it is worthwhile to move forward with it.

3.8.1 Benefits of the project

1. Problem-solving: Because tacit knowledge is frequently anchored in experience, those who possess it typically have an intuitive sense of how to address issues that may be difficult to resolve through the use of formal methods or procedures. This can be especially helpful when repairing locomotives and DMUs because there may be unforeseen problems and a need to act quickly.
2. Efficiency: People who possess tacit knowledge frequently come up with shortcuts, solutions, and other methods that can speed up and improve the efficiency of their work. When repairing locomotives and DMUs, where time is frequently of the essence, this might be especially helpful.
3. Quality: Additionally useful in ensuring high standards of performance are met during operations is tacit knowledge. People that possess tacit knowledge may be able to spot small problems that could have a detrimental influence on quality and may be familiar with simple fixes.
4. Innovation: Tacit knowledge can be an important source of innovation. People who possess tacit knowledge may be able to spot possibilities to improve systems or processes and may be able to come up with innovative solutions that would not be obvious to people who do not possess that information.
5. Knowledge Retention: In a unique work environment of rail operations tacit knowledge is crucial to the success of the Nairobi Central Workshop. The knowledge used and gained in the workshop may not be available anywhere else hence it is important for older employees to pass their experience to younger employees. With Rail bot this knowledge will be retained after employees retire and can be accessed any other time when needed.

3.8.2 Risks of the project

1. Technological difficulties: The voice bot's development and implementation for rail operations may involve technical difficulties, such as making sure the voice bot can correctly understand staff demands and reply accordingly.
2. Information security: Information about KR operations is being gathered and stored, which creates privacy and security concerns that, if not adequately addressed, might become a significant problem.
3. Negative impact on human jobs: Other employees who are hired for consulting work may lose their jobs as a result of the voice bot's implementation.

3.8.3 Mitigation strategies:

1. Technical issues: Before the voice bot is released, a thorough testing approach can help to uncover and address technical issues. A voice bot's continued functionality can also be ensured by periodic monitoring and updates.
2. Information Security: Implementing access via AD credentials can assist prevent unauthorized individuals from accessing knowledge.
3. Negative impact on human jobs: Rail companies can think about keeping affected workers on for other positions within the organization or providing a severance payout to those who will be negatively impacted by the voice bot's installation.

3.8.4 Conclusion:

According to the prospective advantages and disadvantages, it seems that the use of voice bots in rail operations could be quite advantageous to the workers. To minimize any unwanted effects, it is crucial to properly analyze and manage the relevant dangers. By implementing strong security protocols, testing and monitoring the voice bot thoroughly, and addressing the potential impact on human jobs, the risks associated with this project can be minimized.

3.9 Ethical Considerations

This research process and outcome will uphold integrity and originality. The study will avoid forms of falsification or plagiarism. It will uphold confidentiality regarding the corporation's operation and personal information. Before the research is conducted ethical approval and permission will be sought From Strathmore University Institutional Ethics Review Committee (SU- IERC), Kenya Railways Corporation, and other relevant authorities. The respondents will be engaged on a voluntary basis and will be made aware that they can withdraw if they so wish. In

addition, they will give consent to the collection and use of the data they provide. To guide their decision to participate they will be given an information sheet that contains information about the research being undertaken. Data given during the course of this study will only be used as per the user's consent. In addition, it data will be used for only what the user consented to. To ensure ethical conduct, the data collection process will be in line with the permission granted for educational research (Burns 2019).

Chapter 4: System Analysis, Design, and Architecture

4.1 Introduction

This chapter covers system analysis, design, and architecture. System analysis involved seeking information to understand Kenya Railways' structure, processes, and procedures. This entailed conversing with Kenya Railway's head of operation who gave a breakdown of the structure and roles of staff in his section. This then led to drilling down to the specific section of operations at the Central workshop. Similarly, the Workshop Manager gave a breakdown of roles and tasks in his section which led to a clear narrowing down to repair of locomotives and DMUs. With the information the research aligned with the daily tasks, different roles, and information flow within the workshop structure. The system design was used to convert the system requisition specification; collected from data collection tools into a format that can be implemented in the systems operations. These requisitions included defined system components, architecture, interfaces, and data in accordance with the user requirements (Tilley 2019). Subsequent sections in this chapter give in-depth details of how system analysis was conducted and achieved through a comprehensive requirements analysis and exploration of system design and architecture.

4.2 Data and Requirements Gathering

Data and requirements were collected using questionnaires and Interviews. Before the actual data collection reconnaissance was done to familiarize with the respondents and inform them of the need for data being collected. This stage involved one on one discussion with first, the strategic level management who is the Central Workshop Manager to discuss the reasons and nature of the data being collected. Secondly was the tactical level management who is the Principle Engineer. He gave more insight on the nature of work done and by whom in the department. He also gave the roles they middle level manager play in ensuring completion of repairs in central workshop. Lastly, the Operational manager who is the locomotive coordinator. He directly deals with the day to day activities performed by the technicians under their respective supervisors. Repair of Locomotives and DMU's can be classified as either electrical or Mechanical hence there are technicians that specialize in both areas.

With the reconnaissance complete, the data collection begun with filling in questionnaires. Questionnaires were to be issued to all staff involved in repair of locomotives and DMU's. There was need to sensitize the respondents that were not featured in the reconnaissance after which the

questionnaires were issued to the supervisors distributed to the technicians. The same occurred with the engineers. Five engineers submitted the answered questionnaires on the same day of issuing. The other twenty four which were issued to operational level were submitted after two days. This is due to their nature of work which involves hands on engines thus they could only fill the questionnaires at designated times. The questionnaire gathered data on existing sources of tacit knowledge, the procedure of acquiring it and the challenges in acquiring it. In addition it featured how tacit knowledge is currently acquired and from whom.

4.3 Data Analysis

4.3.1 Questionnaire

The Questionnaire targeted has a total of 29 respondent staff Kenya Railways Nairobi Central Workshop. The data collected informed the available sources of tacit knowledge and the causes of challenges in sharing the tacit knowledge. On sources of tacit knowledge among the respondents, 87% percent of them are in the locomotives section where repair of locomotives and DMUs occur with 76%working as technicians and 10% as engineers. 76% of the staff have been employed for more than 10 years.

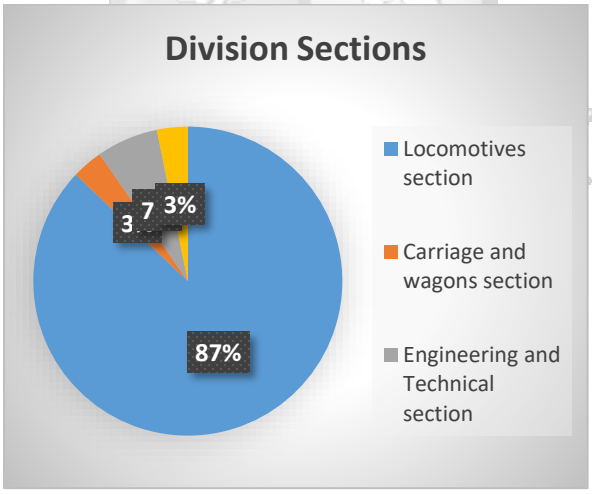

Figure 4. 1: Respondents sections

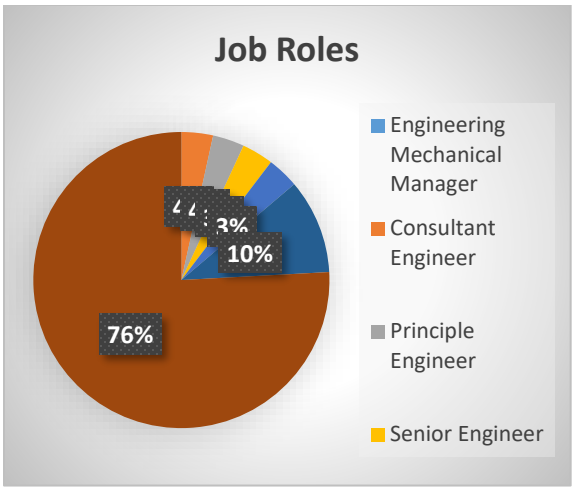

Figure 4. 2: Respondents roles

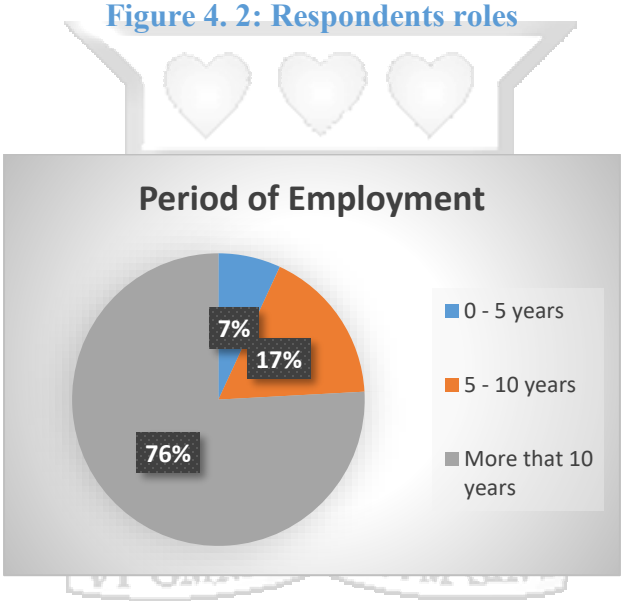

Figure 4. 3: Employment period

100%of the respondents agreed induction is important while 83% agreed orientation alone is not sufficient for a younger employee. This shows other sources of knowledge used in the day-to-day work are required. 41% said they acquire their knowledge through consultation with experienced employees, while 39% get the knowledge from existing Manuals and 20% through modification and testing. Among the sources of knowledge, the most useful source was Consultation from experienced employees with 44% followed by Manuals with 36% and modification and testing with 20%.

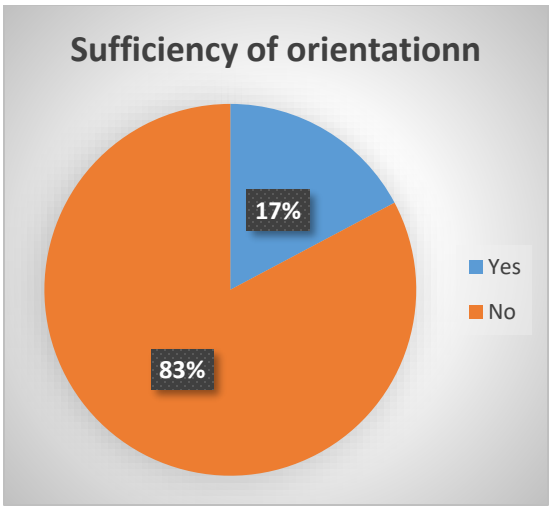

Figure 4. 4: Sufficiency of orientation

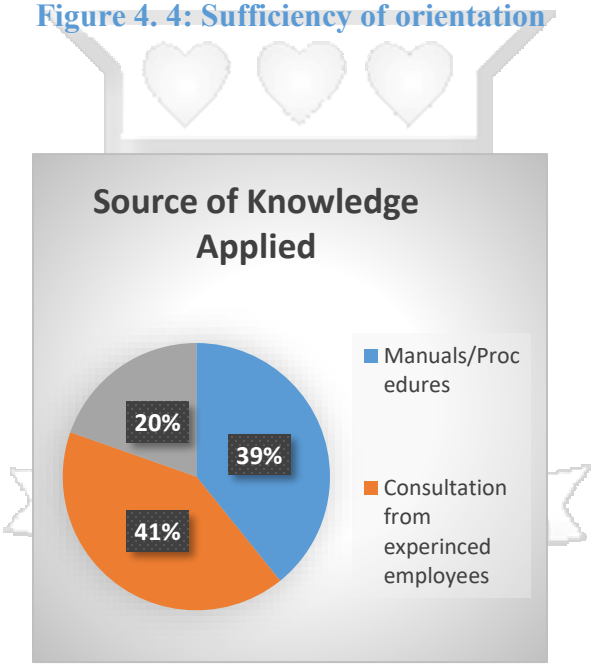

Figure 4. 5: Sources of knowledge

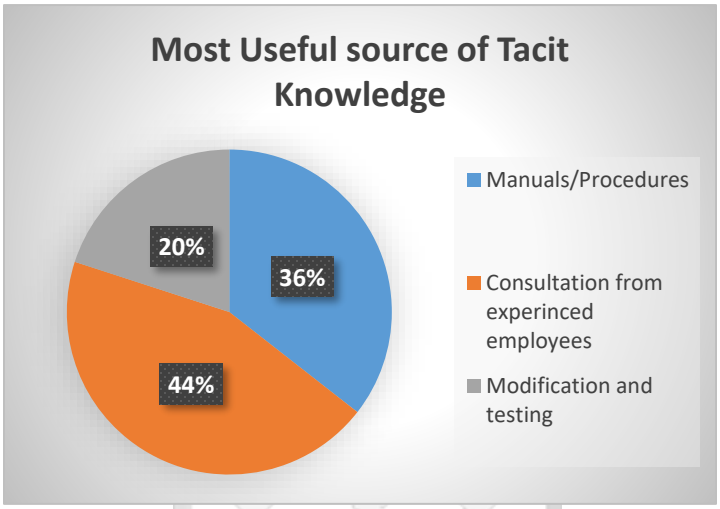

Figure 4. 6: Most used source of knowledge

Among the staff, they often consult fellow technicians, and if a solution isn't found the issue is escalated to the supervisor, principal engineer, consultant engineer, and the top Engineering Mechanical manager.

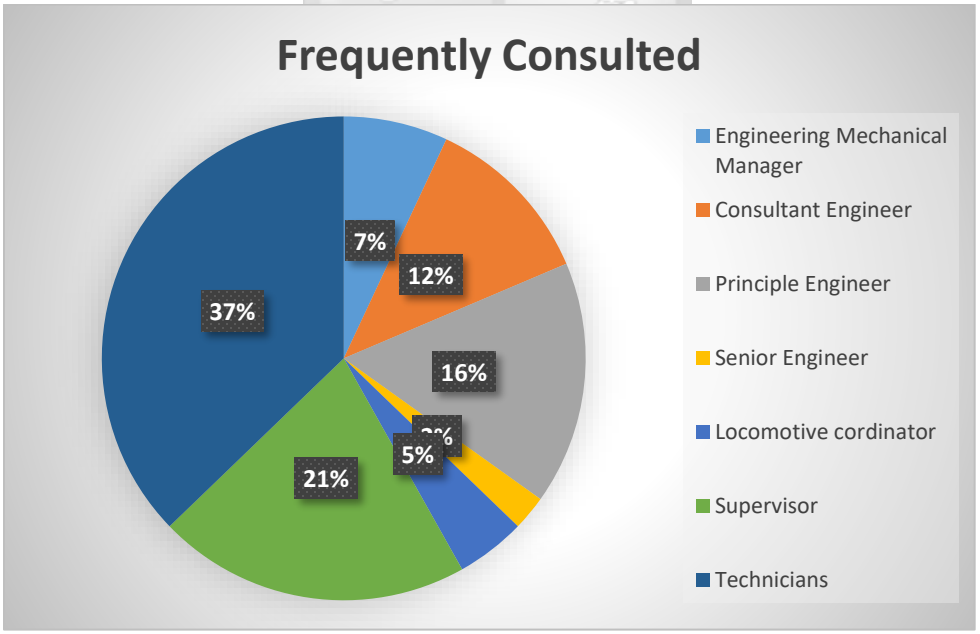

Figure 4. 7: Frequently Consulted staff

In regards to what causes challenges in sharing tacit knowledge, 53% said they always need tacit knowledge in their day-to-day operation and 88% expressed the main challenge is caused by the unavailability of experienced employees when they are required. In addition, when asked what they would change in how they access tacit knowledge, most of the respondents highlighted to increase availability of tacit knowledge.

Figure 4. 8: Need for Tacit Knowledge

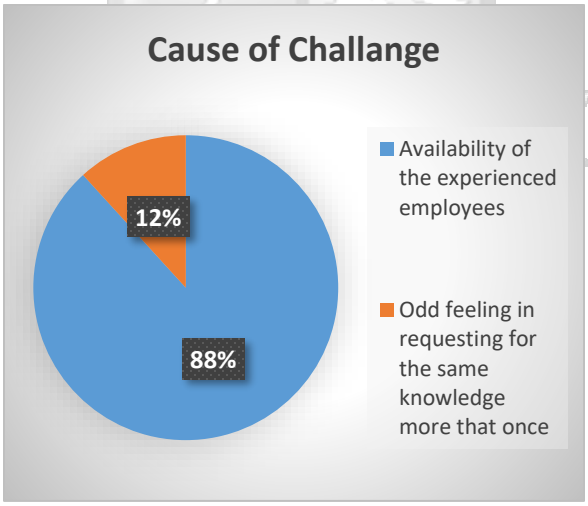

Figure 4. 9: Causes of challenges

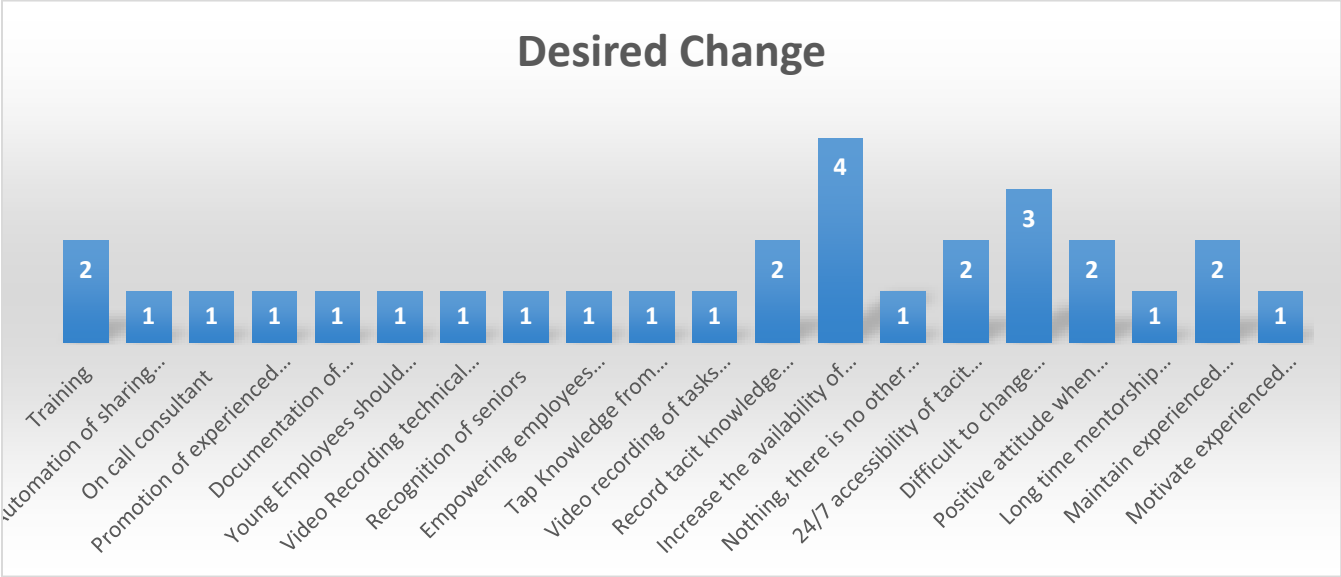

Figure 4. 10: Desired change in sharing tacit knowledge

The interview collected information on the areas where tacit knowledge is required in the day-to-day operations of repairing locomotives and DMUs. Collectively the data gathered represented the system features that must be present in the bot in order to satisfy the operation needs and be acceptable to the users. These requirements were used as a benchmark to measure and test the acceptability functions of the final system (Tilley 2019).

4.3.2 Interviews

Analysis of the data from questionnaire showed that the staff at the workshop often consult fellow technicians, and senior staff for tacit knowledge. They often consulted those who carry more experience on how work is to be done in the workshop. The interview therefore focused on the most experiences staff in the workshop who include one mechanical technician who has been employed for 40 years, one electrical technician employed for over 30 years and one principle mechanical/electrical engineer who has been employed for 10 years. The interview covered tacit knowledge required and functionality requirements of Rail Bot. The data collected from the interview guided the development and training of Rail Bot. For the interview to be done the researcher had to seek a date and time the respondents could spare given their busy schedule. In addition considering the fact when they are working on the locomotives it is difficult to engage them because of the noise in the workshop and nature of the job which requires hands on. The

researcher was given a single day to interview the three respondents. The interview was one on one and took approximately 30 minutes with each respondents.

On sources of tacit knowledge the respondents gave their current job role and period of employment. On the tacit knowledge since the respondents are the most consulted for tacit knowledge at the workshop they gave the areas inexperienced employees have frequently consulted on. This is knowledge that is not on any manual hence employees have to consult in order to accurately perform required repair. The tacit knowledge collected was based on previously required tacit knowledge commonly faced while repairing locomotives and DMUs. From the respondents the repair of locomotives are handled based on either electrical or mechanical challenges it is experiencing. The respondents gave procedures, guide on how to handle locomotive once they are brought to the workshop, how to investigate the problem and fix and test functionality of the locomotive. Among the common challenges highlighted were

1. Locomotive not firing/starting
2. Poor pulling power
3. Compressor failure
4. Defective Alternator
5. Mixing of water and oil
6. Wheel Slip
7. Locomotive not changing direction
8. Traction Motor Failure
9. Ground Fault
10. Heavy Black Smoke
11. Replacement of Cylinder Assembly

On the functionality requirements the respondents shared on both the preferred functional and non-functional requirement.

These features were ranked from the top most being the most required

1. The bot is accessible via the website
2. The bot communicates using audio
3. The bot seeks clarification on the feedback it has

4. The bot seeks support when faced with a question it cannot answer
5. The bot rephrases the user's input
6. The bot identifies the staff details and history
7. The bot allows users to log in with their credentials
8. The bot initiates a conversation
9. The bot stores the context of a successful conversation

On the functionality non-functional requirement the features were ranked from the top most being the least most required

1. Scalability
2. Availability
3. Reliability
4. Security
5. Usability
6. Performance
7. Flexibility

4.4 Summary

In summary, a large percentage of the responses confirmed that among their sources of knowledge used at the workshop, the most useful is tacit knowledge obtained from consulting the experienced employees. However, attaining this tacit knowledge is challenged by the availability of the experienced employees. Given the unique nature of operations at the work shop sharing tacit knowledge has become useful to be passed to the new employees joining the workshop. Therefore harnessing this tacit knowledge on a voice bot, allows inexperience employees to access the knowledge without human interaction. This in turn increases availability of tacit knowledge and therefore increasing employee performance.

4.5 Requirement Analysis

4.4.1 Functional Requirements

These requirements define the end users' requirements on the basic behavior and facilities Rail bot should offer. These technical features contributed to systems operations. They are as follows:-

i. To ensure only KR employees get access to the information; the Rail bot should allow and recognize users logging in with their employee credentials.

ii. To assist Rail bot to only process accurate queries and avoid back-and-forth conversations; the Rail bot will confirm users' input before processing.

iii. To allow users to operate the bot hands-free and save time that would be used typing or reading text; the Rail bot will communicate in audio.

iv. To enable the bot to offer solutions to all user queries, in the case the bot has not right answer it will seek support by sending an email to ICT support to get and upload the correct response.

4.4.2 Non-functional requirements

These requirements define functions that assist the system to operate efficiently. They are related to the performance of the system. They were used to increase the system's overall quality and user experience. They are as follows:-

i. Availability – Rail bot ought to be accessible when required since it contains information that is useful to the repairs of locomotives and DMUs.

ii. Scalability – Rail bot should allow the addition of information in order to expand its knowledge base on areas that require tacit knowledge.

iii. Security –Rail bot should be secured especially from outsiders because of the vital information it carries in regards to Kenya Railways' core operations.

iv. Reliability – The information being offered by Rail bot should be accurate since it will guide staff on repair of Locomotives and DMU.

4.6 System Architecture

The system architecture for the proposed voice bot shows a high-level system design, and structure, and how various system parts help the system's functionality be achieved (Hatley et.al., 2013). The parts of the Rail bot and how they are connected as shown in Figure 4.1 below. The suggested system architecture consists of the following elements: users, microphone, google STTS and TTS translation, NLP, Dialog Manager, knowledge base, Email notification and Bots response. The architectural design of Rail bot is shown below in figure 4.11

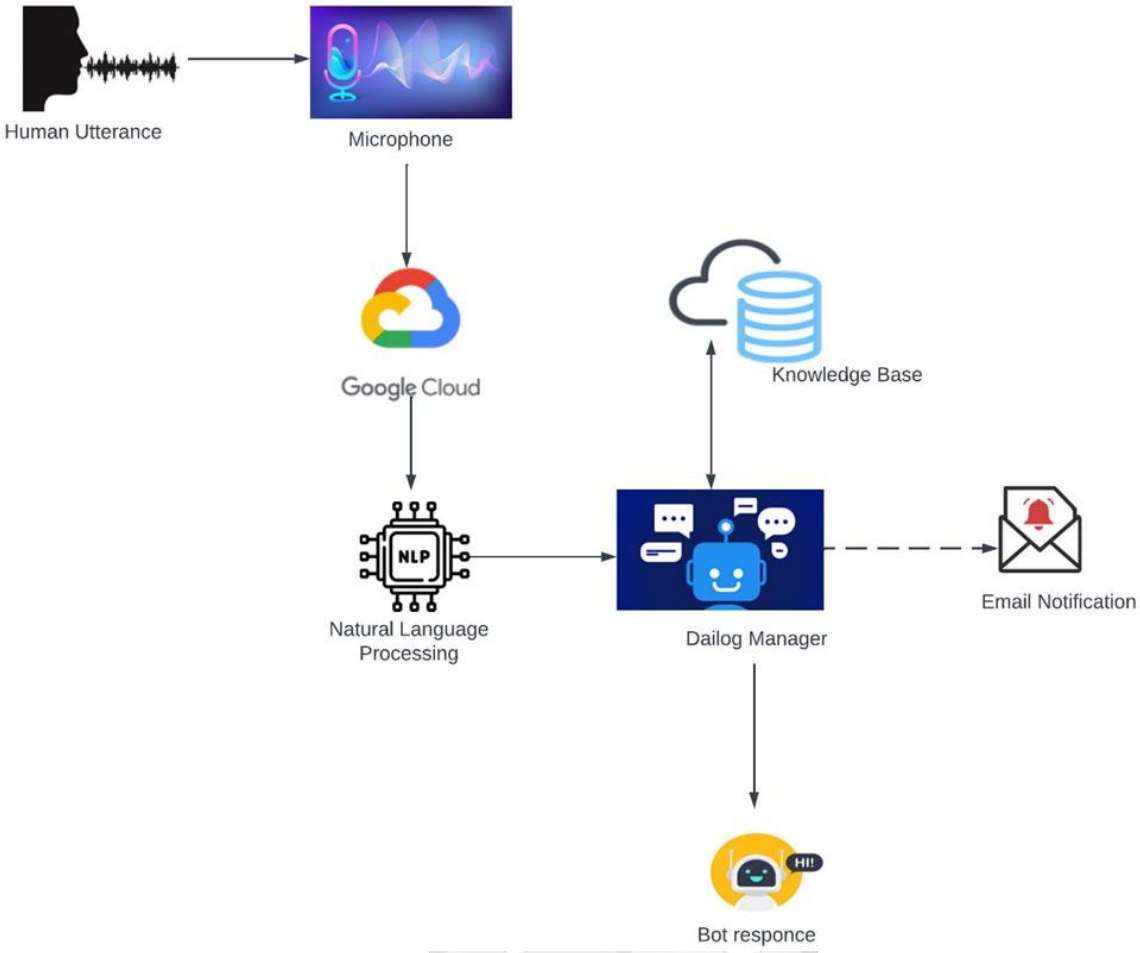

Figure 4. 11: AI Voice Bot System Architecture

4.5 System diagrams

4.5.1 Use Case diagram

Figure 4.12 below illustrates the use case diagram of the proposed system. The actors in the system include the user of the bot and ICT support who works together with the system to achieve the main goal of harnessing tacit knowledge.

Use Case Narration

A textual representation of the proposed system events encounters when the actors interact with Rail Bot

Use Case:

User Login with their staff credentials

Primary Actor

User

Precondition

User must have KR AD credentials

Post Condition

Users' credentials must be complete

Users' credentials must be confirmed to be accurate and valid

Main Success Scenarios

Table 4. 1: User Login with staff credentials

Actor Intention	System Responsibility
1. Staff initiates log in – User name and Password	2. System verifies user credentials by cross-checking with the AD.
	3. System accepts user log in
4. User gets access to the system	

Use Case:

Starts conversation

Primary Actor

User

Precondition

User must initiate a conversation

Post Condition

Users' questions must be audible enough to be captured

Main Success Scenarios

Table 4. 2: User starts the conversation

Actor Intention	System Responsibility
1. User initiates conversation – Speaks to the bot	2. System prompts the user for their request

Use Case:

Generate Response

Primary Actor

Rail bot

Precondition

User must initiate a conversation

Bot must extract intents and entities

Bot must perform pattern matching

Post Condition

Bo must convert generated text into speech

Bot must deliver a response in audio

Main Success Scenarios

Table 4. 3: Rail Bot generates a response

Actor Intention	System Responsibility
1. Rail Bot generates response – responds to the user	2. System converts user input into text
	3. System extracts intent and entities
	4. System does pattern matching for appropriate response

	5. System converts the response into speech for output
	4. System does pattern matching to generate appropriate feedback
5. Output response in audio	

Use Case:

Verify Response

Primary Actor

User

Precondition

Bot must seek approval of response generated

Post Condition

User must confirm whether response is accurate or not

Main Success Scenarios

Table 4. 4: User verifies sufficiency of the response

Actor Intention	System Responsibility
1. User verifies sufficiency of the response	2. System generates verified output

Extension or Alternative Flows

If the user rejects the response the bot seeks support from ICT support to answer the particular request

Use Case:

Seeks Support

Primary Actor

ICT Support

Precondition

The user must confirm generated response as not sufficient after three attempts

The bot is unable to pattern-match users' request

Post Condition

Rail Bot seeks support via email to ICT support

Main Success Scenarios

Table 4. 5: Rail Bot seeks support

Actor Intention	**System Responsibility**
1. Seek support to redetected or not found response	2. Inform the user of intention to seek support
	3. Send an email to ICT support seeking response to users request

Use Case:

Offer Support

Primary Actor

ICT Support

Precondition

Rail Bot must request support on a particular request

Post Condition

ICT support uploads appropriate feedback from the subject experts

Main Success Scenarios

Table 4. 6: User Login with their staff credentials

Actor Intention	System Responsibility
1. Upload appropriate response from subject matter	2. Keep the uploaded response in the knowledge base for related requests.

The use case diagram is as illustrated below:

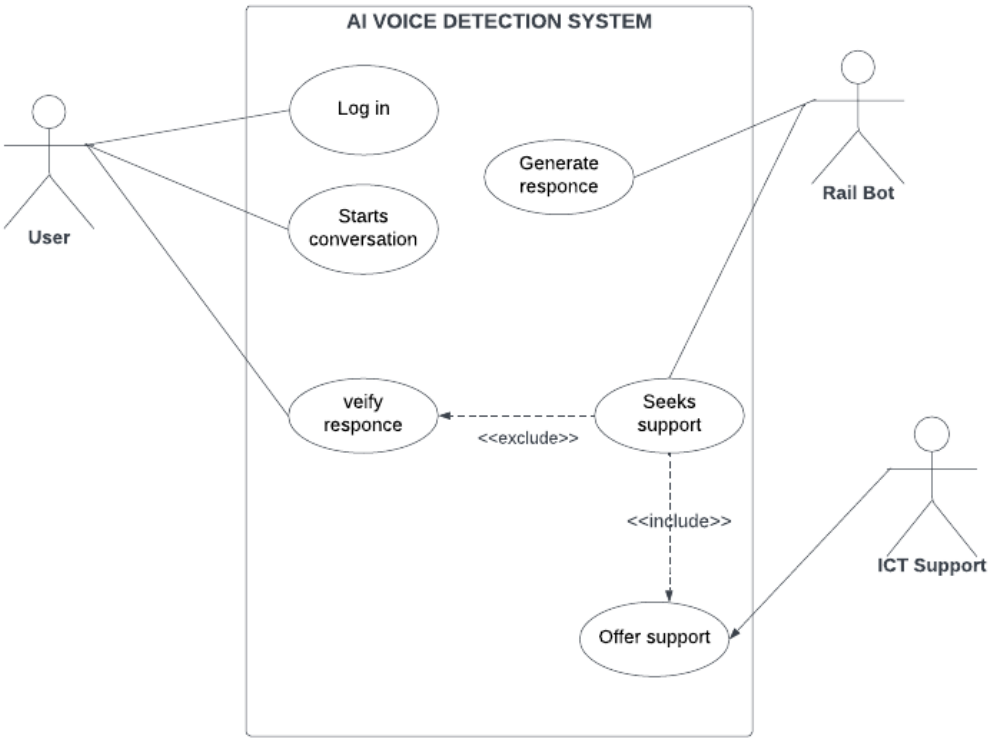

Figure 4. 12: Use Case Diagram

4.5.3 Sequence Diagram

The sequence diagram emphasizes the time sequence of messages and the structural organization of the objects that send and receive messages (Ahmed et.al., 2019). First, the user will enter their login credentials. The login verification will be done if the details are correct then authentication and access will be given. Otherwise, the user will be denied access. After being granted access, the user initiates a conversation with the bot using a general greeting such us hi or hello. The

system requires a user to input a query and the bot will give a response. The system process is as follows: - To begin with, the system requires a user to first log in with their employee credentials on the web portal. They will then initiate the conversation with the bot. Through Automatic Speech Recognition Rail bot will recognize the input and seek query input from the user. Once the user inputs their query Rail bot will use the STT converter to convert the voice input into text for processing. The text will then be converted into the machine-understandable format and begin processing. The message is sent to the NLU. On the NLU the query entered will be tokenized into smaller portions. It will then be classified into intent and entities. These classifications will be used by the dialogue manager to get the user intent and context of the query. Once it gets the intent Rail bot will ask the user to clarify the intention processed. After clarification Rail bot will fetch feedback from its knowledge base and give a response to the user. Through NLG the feedback is converted back to human language and converted to voice by the TTS converter. Finally, Feedback is relayed to the user as audio.

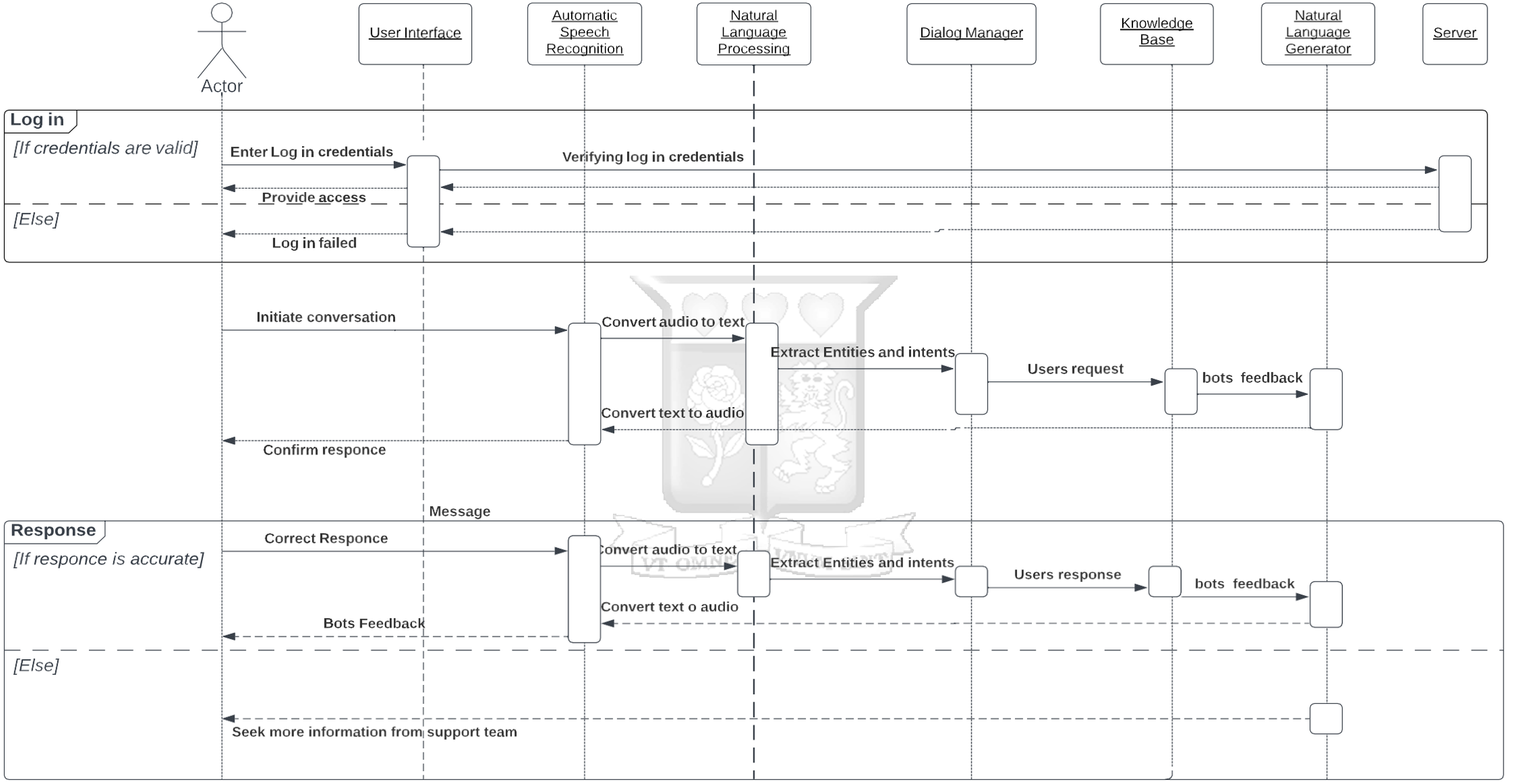

Figure 4. 13: Sequence Diagram

4.5.4 Entity Relationship Diagram

Entity Relationship Diagram (ERD) is used to depict the existing entities in the system database their attributes and the relationships between the various entities (Hatley et.al., 2013). The entities and relationships are as follows:-

Entities:

- Users: represents a person who is interacting with the voice bot.
- Resets: represents information about user password request.
- Settings: represents information on user preference.
- Knowledge: represents the knowledge the bot will use to generate appropriate responses.
- Conversation: represent the flow of conversation between the Rail bot and the user.

Relationships:

- A user can have multiple conversations with the voice bot (one-to-many).
- Knowledge can be used in many conversation (one-to-many).
- A user can have many preferences (One-to-many).
- A user can have many requests to reset password (One-to-many).

This is illustrated in the figure below

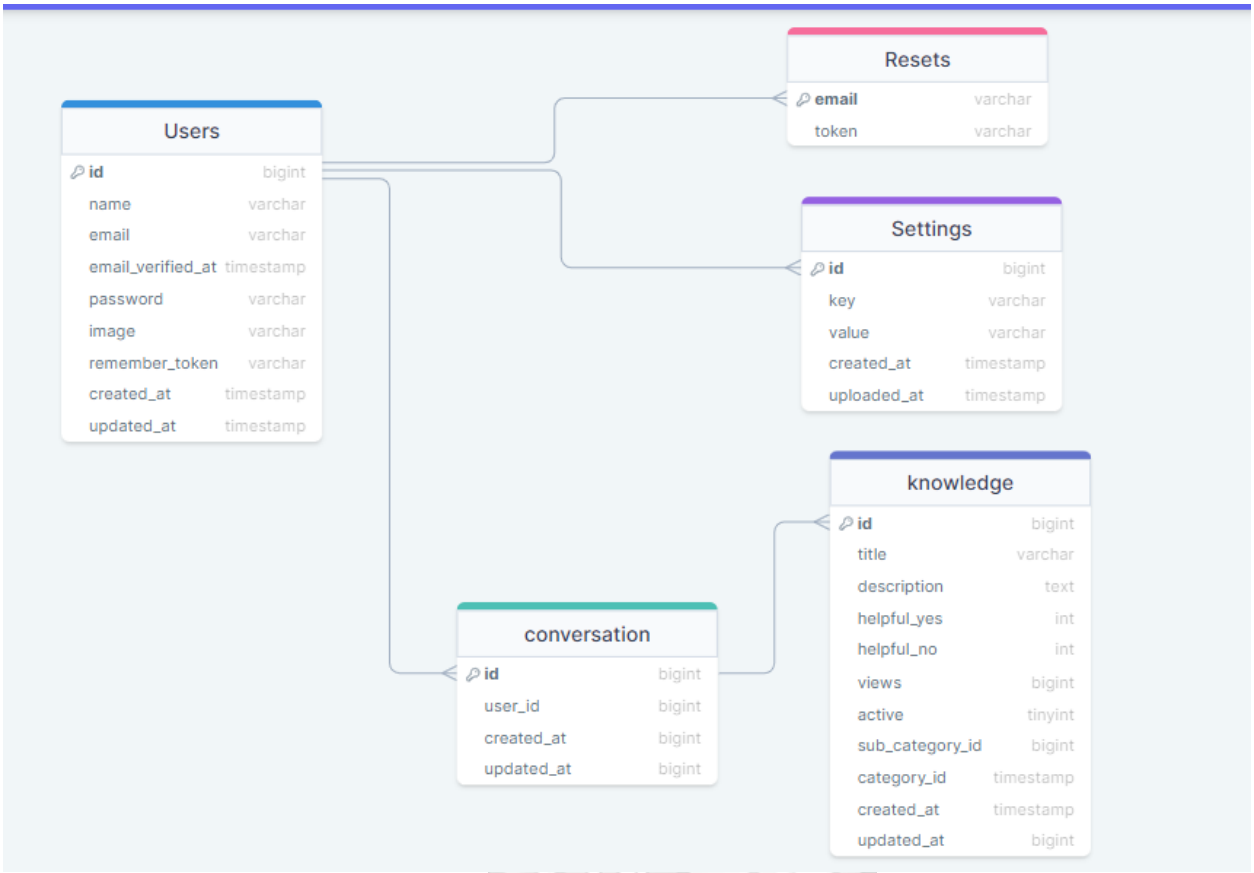

Figure 4. 14: Entity Relationship Diagram

4.5.5 Wire frames

Wireframe is used in the design process to show the architectural blueprint providing a visual representation of the user interface and interactions with the voice bot. In addition, it provides a guide for the development of the final product. The wireframe illustrates the flow of displays when a user is interacting with the Rail bot website. The first step shows the login page which requests the user to input their username, position, and password. The second step is the home page where the user's department is displayed and an icon to initiate conversation with Rail bot.

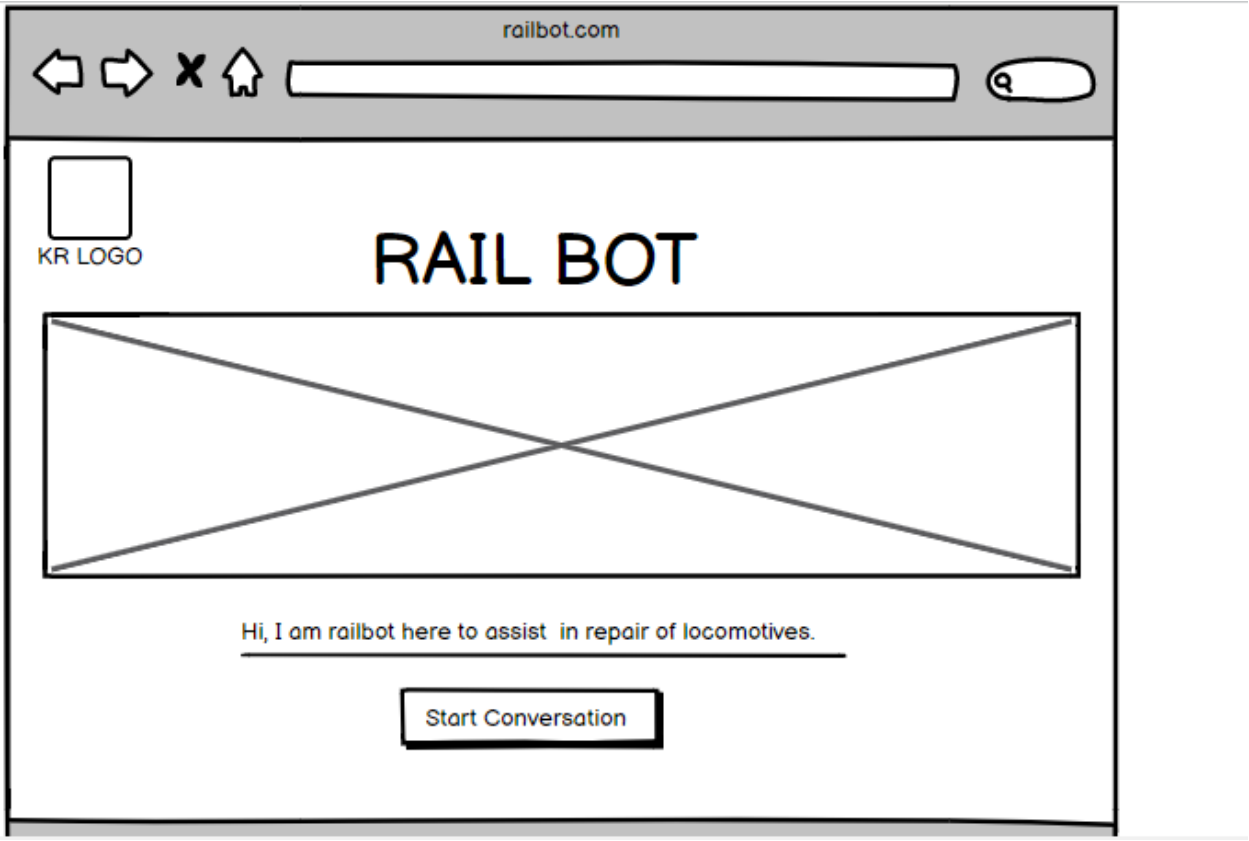

Figure 4. 15: Landing Page

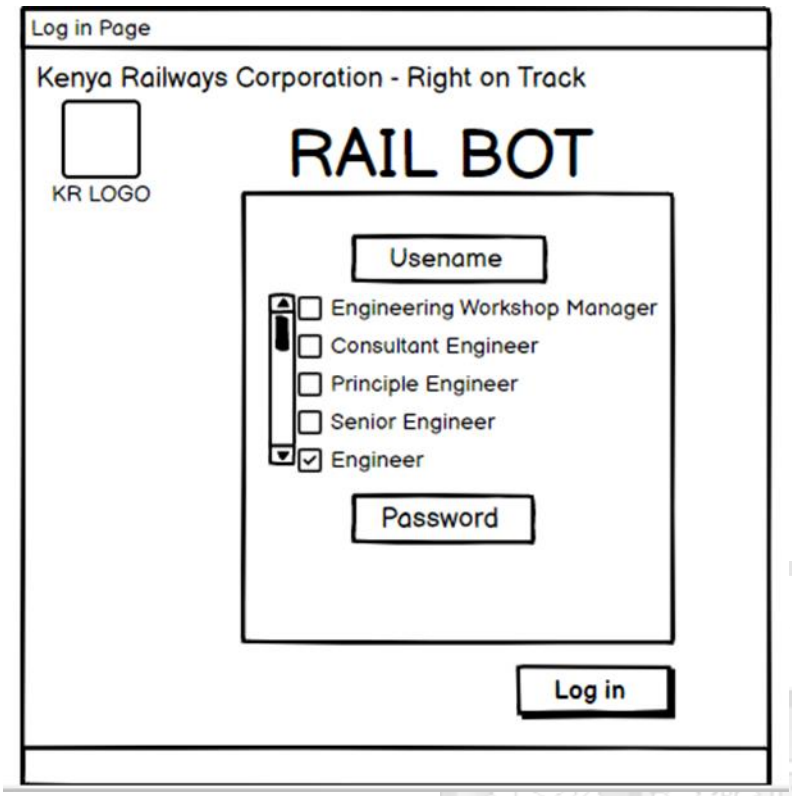

Figure 4. 16: Log in Page

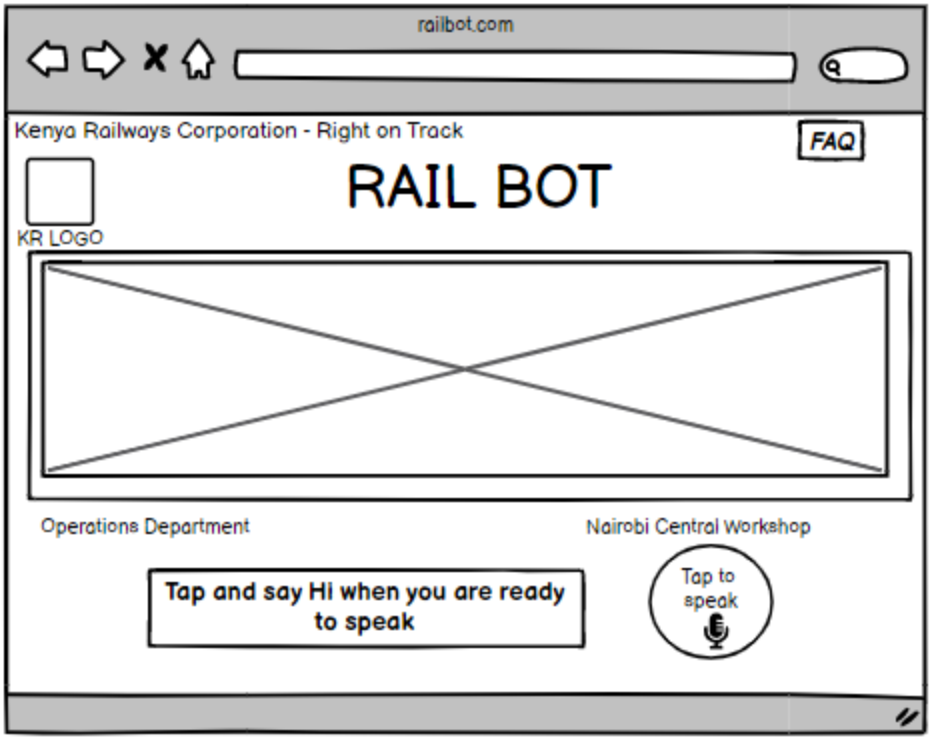

Figure 4. 17: Conversation Page

Chapter 5: System Implementation and Testing

5.1 Introduction

System implementation and testing details the sets of procedures followed to complete the design of the system as per the system analysis and design. The study aimed at developing an AI Voice bot to harness tacit knowledge within the Nairobi central Workshop in repair of locomotives and DMU's. The overall design of the Voice bot, as well as the necessary hardware and software, are described in detail in the following sections. It also describes the process used to create, train, test, and evaluate the bot in order to meet its functional requirements. The main language used to construct the bot was Python.

5.2 System Implementation

5.2.1 Hardware and Software Environment

Rail bot was developed on google colaboratory a cloud based IDE suitable for creating machine learning systems using python. The development will employ Python programming language for the backend logic and PHP for the user interface. The user interface was built on a website. Rail bot was trained using dataset containing questions from junior staff and answers from the expert knowledge from the respondents that was collected from the interviews.

Hardware Requirements

The minimum system requirements developing Rail Bot are:-

1. Laptop computer with Windows 10 operating system
2. The computers' processor speed was 1.19 GHz, a RAM of 8GB, and SSD 512GB

5.2.2 System development

5.2.2.1 Code 1: Audio Input processing

This code does audio processing and converts it into text for processing.

audio, 'sr = get_audio(): This line uses the 'get_audio()' function to capture audio from the microphone and store it in the variable audio. The variable 'sr' contains the sampling rate of the audio (i.e., the number of samples per second).

'fs = sr:' This line sets the variable fs to be equal to the sampling rate sr.

‘out_f’ = 'o.wav': This line creates a new variable ‘out_f ‘and sets its value to 'o.wav', which will be the filename of the output audio file.

‘wavf.write(out_f, fs, audio):’ This line uses the write() function from the ‘wavfile ‘module to write the audio data in audio to a new WAV file with the filename specified in ‘out_f’. The sampling rate fs is also passed as an argument to the function. The resulting WAV file will be saved in the current working directory

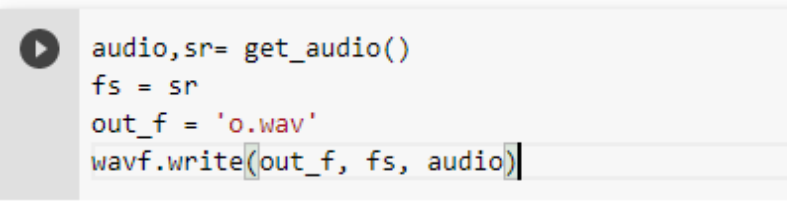

Figure 5. 1: Code for audio input processing

5.2.2.2 Code 2: Speech Recognition

This code installs two libraries: ‘Speech Recognition’ and ‘pydub’. It then imports these libraries as well as the os library. It also imports two functions from the ‘pydub’ library: Audio Segment and ‘split_on_silence’.

Next, the code defines a function called get_large_audio_transcription () which takes a path to an audio file as an argument. This function splits the audio file into chunks based on silence and applies speech recognition to each chunk. Specifically, it reads in the audio file using pydub, splits the audio file into chunks where silence is greater than or equal to 500 milliseconds using the split_on_silence() function, and stores each chunk in a directory called "audio-chunks".

For each chunk, the code exports the chunk as a .wav file, reads in the chunk using the Speech Recognition library, and tries to convert the chunk to text using the recognize google() method. If the method fails to recognize the chunk, an error message is printed. If the method succeeds, the text is capitalized, printed along with the filename of the chunk, and added to the whole_text variable.

Finally, the function returns the full text of all the chunks detected. The code then sets the path variable to the location of an audio file called "o.wav" and prints out the full text of that audio file by calling the get_large_audio_transcription() function with the path variable as an argument.

```
!pip3 install SpeechRecognition pydub
import speech_recognition as sr
import os
from pydub import AudioSegment
from pydub.silence import split_on_silence

# create a speech recognition object
r = sr.Recognizer()

# a function that splits the audio file into chunks
# and applies speech recognition
def get_large_audio_transcription(path):
    """
    Splitting the large audio file into chunks
    and apply speech recognition on each of these chunks
    """
    # open the audio file using pydub
    sound = AudioSegment.from_wav(path)
    # split audio sound where silence is 700 miliseconds or more and get chunks
    chunks = split_on_silence(sound,
        # experiment with this value for your target audio file
        min_silence_len = 500,
        # adjust this per requirement
        silence_thresh = sound.dBFS-14,
        # keep the silence for 1 second, adjustable as well
        keep_silence=500,
    )
```

Figure 5. 2: Code Split input audio into chucks

```
[ ]     folder_name = "audio-chunks"
        # create a directory to store the audio chunks
        if not os.path.isdir(folder_name):
            os.mkdir(folder_name)
        whole_text = ""
        # process each chunk
        for i, audio_chunk in enumerate(chunks, start=1):
            # export audio chunk and save it in
            # the `folder_name` directory.
            chunk_filename = os.path.join(folder_name, f"chunk{i}.wav")
            audio_chunk.export(chunk_filename, format="wav")
            # recognize the chunk
            with sr.AudioFile(chunk_filename) as source:
                audio_listened = r.record(source)
                # try converting it to text
                try:
                    text = r.recognize_google(audio_listened)
                except sr.UnknownValueError as e:
                    print("Error:", str(e))
                else:
                    text = f"{text.capitalize()}. "
                    print(chunk_filename, ":", text)
                    whole_text += text
        # return the text for all chunks detected
        return whole_text

    path = "o.wav"
    print("\nFull text:", get_large_audio_transcription(path))
```

Figure 5. 3 Code to convert audio into text

5.2.2.3 Code 3: Greetings

For a user to engage Rail bot they must initiate the conversation preferably with a greeting. This code is used to recognize greeting. The purpose of the function is to enable Rail bot understand and respond to greeting messages which will make it more engaging and interactive

This code defines a function named "greeting" that takes a sentence as input and checks if the input contains a greeting message. The function compares each word in the input sentence to a predefined tuple of greeting words, such as "hello Rail bot", "hi Rail bot ", "greetings Rail bot ", and "hey Rail bot " among others.

If the input sentence contains a greeting word, the function randomly selects a response message from another predefined list of greeting response messages, such as "hi", "hey", "hi there", and "hello". The function then returns the selected response message.

```
[10] # Keyword Matching
     GREETING_INPUTS = ("hello Railbot", "hi Railbot", "greetings Railbot", "sup Railbot", "what's up Railbot","hey Railbot")
     GREETING_RESPONSES = ["hi", "hey", "*nods*", "hi there", "hello", "I am happy to talk to you"]
     def greeting(sentence):
         """If user's input is a greeting, return a greeting response"""
         for word in sentence.split():
             if word.lower() in GREETING_INPUTS:
                 return random.choice(GREETING_RESPONSES)
```

Figure 5. 4: Code for Greeting Function

5.2.2.4 Code 4: Data Processing

For Rail bot to understand users' inputs it need to process data received. This is done by tokenization, Lemmatization and Normalization. These techniques are used in data processing to convert raw input text into a format that is can be used for NLP tasks such a text classification, sentiment analysis and response generation.

This code involves tokenization of the text using the Natural Language Toolkit (NLTK) library in Python. The text is first split into sentences using the 'sent_tokenize' method and stored as a list of sentence strings in the 'sent_tokens' variable. The text is then split into individual words using the 'word_tokenize' method and stored as a list of word strings in the 'word_tokens' variable.

The code then defines a function named 'LemTokens' that takes a list of tokens (i.e., words) as input and applies lemmatization to each token using the 'WordNetLemmatizer' from the NLTK library. The lemmatized tokens are then returned as a list.

The next block of code defines a dictionary named 'remove_punct_dict' that maps each punctuation character to none. This dictionary is then used to remove all punctuation characters from the text by calling the translate method on the lowercase text string and passing in the 'remove_punct_dict' dictionary. The resulting text string is then passed to the 'LemNormalize 'function, which applies the 'LemTokens' function to the tokenized text and returns a list of lemmatized word strings. This function is intended to preprocess the text for use in natural language processing tasks such as topic modeling, sentiment analysis, or chatbot response generation.

```
from google.colab import drive
drive.mount('/content/drive')

path = "/content/drive/MyDrive/"

#Reading in the input_corpus
with open(path+'intro_join.txt','r', encoding='utf8', errors ='ignore') as fin:
    raw = fin.read().lower()
#TOkenisation
sent_tokens = nltk.sent_tokenize(raw)# converts to list of sentences
word_tokens = nltk.word_tokenize(raw)# converts to list of words
# Preprocessing
lemmer = WordNetLemmatizer()
def LemTokens(tokens):
    return [lemmer.lemmatize(token) for token in tokens]
remove_punct_dict = dict((ord(punct), None) for punct in string.punctuation)
def LemNormalize(text):
    return LemTokens(nltk.word_tokenize(text.lower().translate(remove_punct_dict)))
```

Figure 5. 5: Code for data processing

5.2.2.5 Code 5: Searching for response

This code defines a loop that takes voice input and processes it using a classifier. The loop continues running as long as the flag variable is true.

Inside the loop, the user's response is processed using a classifier to determine the type of dialogue act being performed (such as a greeting, a question, or an emotion). If the dialogue act is not "Bye", the code checks if it is a greeting, and if so, responds accordingly. If it is not a greeting, the code generates a response using a response function, removes the user's response from a list of sentence tokens, and sets the flag to False to exit the loop.

If the dialogue act is "Bye", the code prints a message and sets the flag to False to exit the loop.

After the loop, the code uses Google Text-to-Speech (gTTS) to convert the response to an audio file, saves the audio file, and then plays the audio file.

```
flag=True
# Taking voice input and processing
while(flag==True):
  user_response = format(a)
  print("\033[91m {}\033[00m" .format("YOU SAID : "+user_response))

    #user_response = input()
    #user_response=user_response.lower()
  clas=classifier.classify(dialogue_act_features(user_response))
  if(clas!='Bye'):
    if(clas=='Emotion'):
      flag=False
      prBlack("Diana: You are welcome..")
      ans="Diana: You are welcome.."
    else:
      if(greeting(user_response)!=None):
        flag=False
        print("\033[93m {}\033[00m" .format("Diana: "+greeting(user_response)))
        ans=greeting(user_response)
      else:
        print("\033[93m {}\033[00m" .format("Diana: ",end=""))
        res=(response(user_response))
        ans=res
        prBlack(res)
        sent_tokens.remove(user_response)
        flag=False
```

5.2.2.6 Code 6: Response Generation

The function takes in a ‘user_response’ as an argument, which is a string of text input by the user. The function then appends the ‘user_response’ to the sent_tokens list, which contains a list of previously inputted sentences.

Next, the function uses the ‘TfidfVectorizer’ from the ‘scikit-learn’ library to calculate the TF-IDF (Term Frequency-Inverse Document Frequency) of the ‘sent_tokens’ list. TF-IDF is a statistical measure used to evaluate the relevance of a word in a document based on its frequency in the document and the frequency of the word in the entire corpus of documents. The cosine similarity is then calculated between the ‘user_response’ and each sentence in the ‘sent_tokens’ list to determine which sentence is most similar to the ‘user_response’.

The function then returns a ‘robo_response’, which is either an appropriate response to the ‘user_response’ or an apology if the bot doesn't understand the user's input. If the ‘req_tfidf’ value is zero, the function returns the message "I am sorry! I don't understand you". If ‘req_tfidf’ is not

zero, the function returns the sentence from ‘sent_tokens’ that has the highest cosine similarity with the ‘user_response’, as determined by the ‘idx value’.

```
# Generating response and processing
def response(user_response):
    robo_response=''
    sent_tokens.append(user_response)
    TfidfVec = TfidfVectorizer(tokenizer=LemNormalize, stop_words='english')  #Calculate document vector
    tfidf = TfidfVec.fit_transform(sent_tokens) #Calculate tf-idf for the given document
    vals = cosine_similarity(tfidf[-1], tfidf)  #Calculate the Cosine Similarity
    idx=vals.argsort()[0][-2]
    flat = vals.flatten()
    flat.sort()
    req_tfidf = flat[-2]
    if(req_tfidf==0):
        robo_response=robo_response+"I am sorry! I don't understand you"
        return robo_response
    else:
        robo_response = robo_response+sent_tokens[idx]
        return robo_response
```

Figure 5. 6: Code for generating response

5.2.2.7 Code 7: STT conversion

This code uses the gTTS library from Google to convert a string of text to speech and save it as an audio file.

First, the gTTS method is used to convert the string "My name is Railbot. I will answer your queries about Repair. If you want to exit, say Bye" to speech.

Next, the save method is used to save the speech as an audio file named "file.mp3".

Finally, the Audio method from IPython's Display Class is used to play the saved audio file. The autoplay parameter is set to True, which means that the audio file will automatically play when the code is executed. If you don't want the audio file to play automatically, you can set autoplay to False.

```
from gtts import gTTS #Import Google Text to Speech
from IPython.display import Audio #Import Audio method from IPython's Display Class
tts = gTTS('My name is Railbot. I will answer your queries about Loco and DMU Repair.
If you want to exit, say Bye') #Provide the string to convert to speech
tts.save('file.mp3') #save the string converted to speech as a .wav file
sound_file = 'file.mp3'
Audio(sound_file, autoplay=True)

#Autoplay = True will play the sound automatically
#If you would not like to play the sound automatically, simply pass Autoplay = False.
```

Figure 5. 7: Code for STT conversion

5.3 System Training

NLTK was used as a training environments for the tool. This is because it provides a wide range of powerful tools and resources such as Naïve Bayes which was used for classifying text (users input based on the training dataset). In addition, NLTK provides a pre-trained Naïve Bayes classifier on a NPS Chat corpus. The Naval Postgraduate School (NPS) hosts an online chatroom, which is where the NPS conversation corpus is a collection of conversation messages from that room. It includes discussions using diverse chat message formats, such as greetings, remarks, and questions, as well as dialogues on a range of subjects. These compiled chats were used as a benchmark dataset to evaluate NLP techniques and ML algorithms for tasks such as classification, tokenization, sentiments analysis, and more (Brownlee, 2017 and Kamath et al., 2019). The knowledge dataset as shown in figure 5.8 was then populated on the corpus to serve as a dataset for the bot to learn from and develop its ability to recognize and respond to user inputs. The knowledge dataset was obtained from the responses of the interview which highlighted the frequently consulted areas and the solutions.

What is a Wheel Slip
Definition: When the engine of the locomotive runs it excites the generator, the generator gives voltage and the traction motors demand to pull the load. For a locomotive to move we have six traction motors. The traction motors are driven by power from the main generator. When power does not reach the traction motor then is called a wheel sleep.

Fixing wheel sleep
- Check whether the Voltage from the generator reaches the traction motor
- Check for an open circuit in the lines between the generator and traction motors
- Check if either of the traction motors has an open circuit
- If a traction motor has an issue, disconnect the motor from the superstructure
- Replace it with a well-serviced motor, test it
- If working well release the Locomotive

Locomotive not firing on
- Check the process of starting the locomotive
- Prime the locomotive
- Press the start button
- Check whether two conductors called CK (negative and positive) are coming in
- This will cause the engine to rotate
- Once it rotates the engine fires on.
- If the engine does not rotate call the mechanical engineers to check, if the conductors are not going in check the electrical components.

What is priming -Check if the motor is pulling oil from the fuel tanks to the fuel gallery of the combustion chamber

Locomotive not changing direction
- Check if the reverser switch is changing direction
- Check the conductor coils are well terminated.
- Check whether the conductor coils are getting energized
- Check the reverse handles

How does a locomotive change direction work?
When you select the direction the coils are energized. It is forward it energizes the coils for forward direction then the coil will open, air passes through and the diaphragm will make the reverser switch to change direction. Same applies Vise Versa

Figure 5. 8: Corpus - Knowledge Dataset

Code 1: Set – up for training

The code will load the posts from the corpus in XML format and assigns them to the variable "posts". Once loaded, the "posts" variable is used to analyze the chat data using various natural language processing techniques provided by the NLTK library, such as tokenization, stemming, part-of-speech tagging, sentiment analysis, and more. Then, it defines a function named "dialogue_act_features" that tokenizes the input text and generates a dictionary of features that indicate whether the input contains specific words or not.

Next, the code applies this function to each post in the selected dataset, generating a list of feature sets, where each feature set consists of a dictionary of features and the corresponding dialogue act class of the post (i.e., "Question", "Statement", "Greeting", etc.).

Afterward, the code splits the feature sets into a training set and a testing set, using 90% for training and 10% for testing.

Finally, the code trains a Naive Bayes classifier using the training set and evaluates its performance on the testing set. Once trained, the classifier can be used to predict the dialogue act of new text inputs as either a question or not.

```
posts = nltk.corpus.nps_chat.xml_posts()[:10000]
# To Recognise input type as QUES.
def dialogue_act_features(post):
    features = {}
    for word in nltk.word_tokenize(post):
        features['contains({})'.format(word.lower())] = True
    return features
featuresets = [(dialogue_act_features(post.text), post.get('class')) for post in posts]
size = int(len(featuresets) * 0.1)
train_set, test_set = featuresets[size:], featuresets[:size]
classifier = nltk.NaiveBayesClassifier.train(train_set)
```

Figure 5. 9: Code to Install Corpus

The algorithm works by first learning the probabilities of each feature in the training data for each class (e.g., positive or negative sentiment). Then, when given a new input text, the algorithm calculates the probability of the input belonging to each class based on the learned probabilities of the features in that input. The class with the highest probability is then assigned as the predicted class for the input.

Despite its "naive" assumption, Naive Bayes has been shown to perform well in many text classification tasks, particularly when the number of features is large relative to the number of training examples. It is also computationally efficient and requires relatively little training data compared to other machine learning algorithms (Brownlee, 2017).

5.4 System Testing

Testing Rail Bot was done to ensure it is functioning correctly and delivering a high-quality user experience Pandey et al. (2021). When a user inputs their question in audio it is converted to text then processed as shown in figure 5.10

```
Full text: What is a wheel slip.

[25] a=get_large_audio_transcription(path)

audio-chunks/chunk1.wav : What is a wheel slip.
```

Figure 5. 10: Processed user input

Rail bot will the paraphrase the user input to confirm their request and then give the most appropriate response as show on figure 5.11. According to the data on the corpus in figure 5.8 the bot extracted precisely what the user requested.

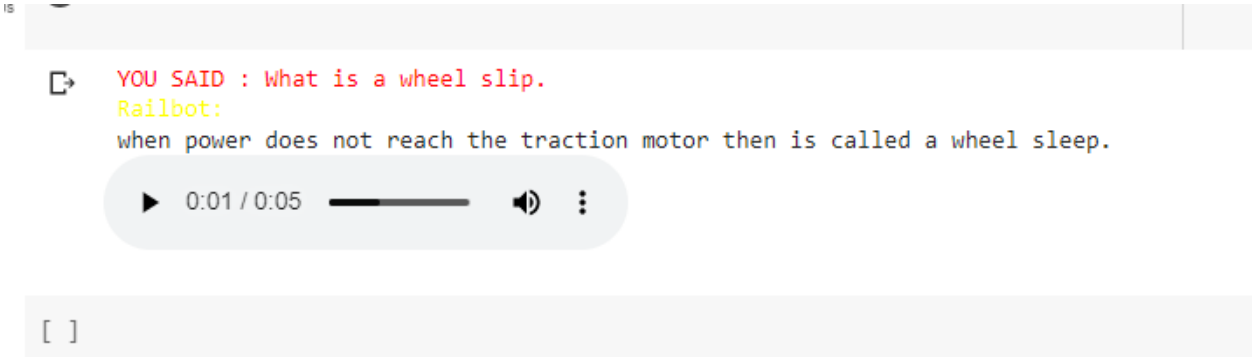

Figure 5. 11: User Output

5.5 System Validity

System Validity was performed to check the validity of the voice bot in ensuring that the system is reliable and can deliver a high-quality user experience. The validity step included a user accessing Rail bot via a web interface as shown in figure 5.12. This page introduced the user to Rail bot.

Figure 5. 12: Home Page

When the user understood the purpose of Rail bot the user chose to start a conversation where they were required to register as user as shown in figure 5.13.

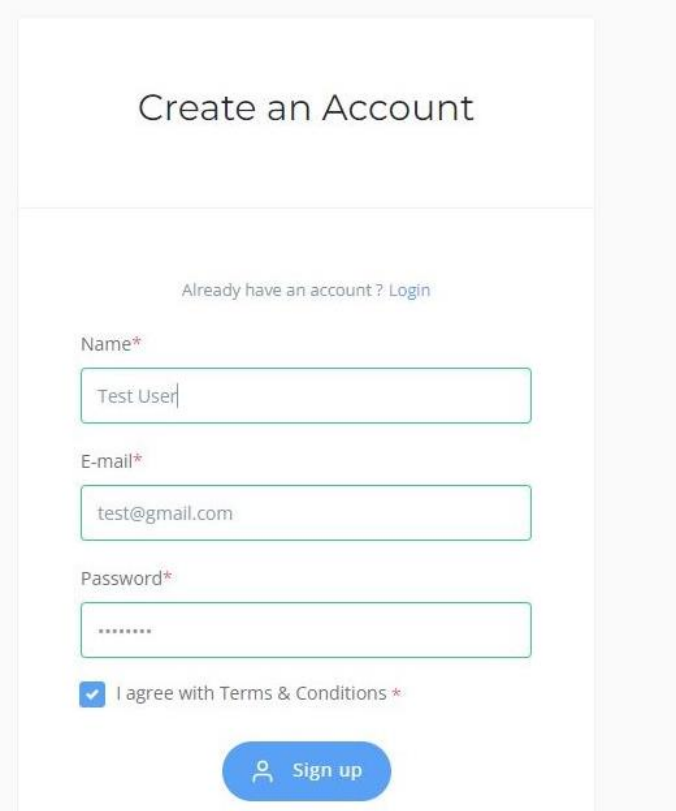

Figure 5. 13: User Registration

After the registration the user can now be identified and is then led to the conversing page where by tap the microphone they start conversing with Rail bot as shown in figure 5.14

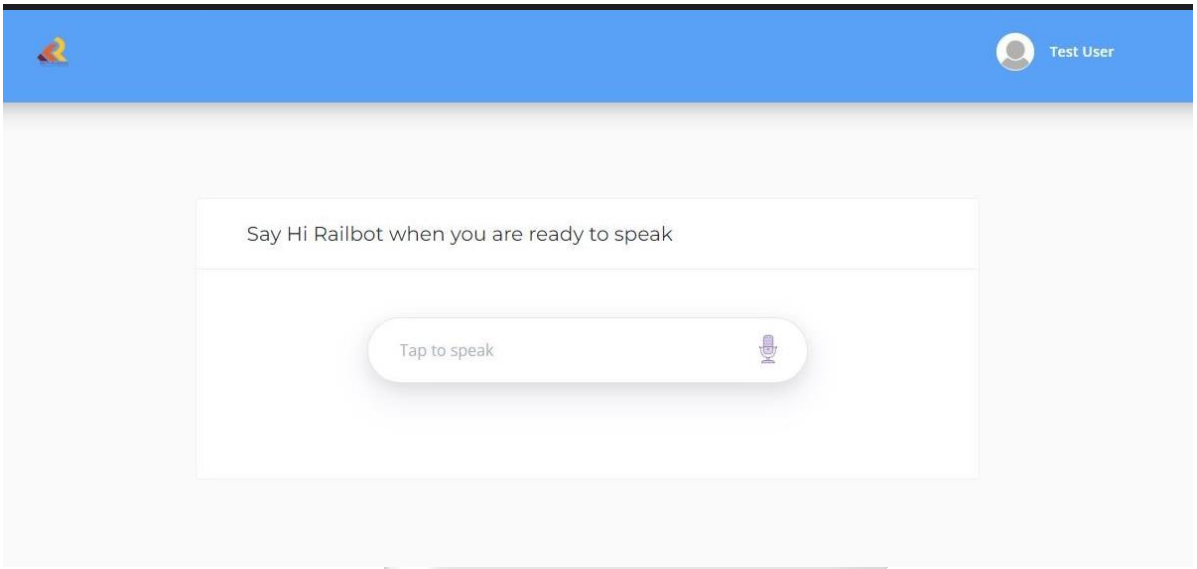

Figure 5. 14: Conversing Page

Chapter 6: Discussion

6.1 Introduction

This chapter discusses the results of the developed solution in light of the objectives and research questions outlined in chapter one. The main objective of this study was to develop a tool to harness tacit knowledge to improve employee performance in Kenya Railways using AI voice detection. The study targeted tacit knowledge shared at the Nairobi Central workshop in the repair of locomotives and DMUs. The tool uses voice recognition to be able to have conversations with users in audio. The tool which was named Rail Bot was trained using tacit knowledge collected from experts in the workshop in regard to their operations. As mentioned in the problem statement Rail Bot responds to challenges in sharing and accessing tacit knowledge among the employees. Rail bot has made tacit knowledge accessible anytime anywhere and even when experienced employees exit the organization the knowledge will still be available through Rail bot knowledge base.

6.2 Results

6.2.1 Sources of Tacit Knowledge

As per the literature review in chapter two according to Hadjimichael and Tsoukas, (2019), tacit knowledge is the knowledge that is difficult to express and formalize, as it is embedded in an individual's personal experiences, skills, and intuition. The authors contend that in tasks like running a machine, where a person's competence and experience are crucial for success, tacit knowledge is especially significant. In these circumstances, people rely on their tacit knowledge to decide what to do and how to do it without explicit instruction or documentation. It is difficult to codify and transmit tacit knowledge to others since it is ingrained in a person's own experience and intuition and is frequently communicated through nonverbal signs, intuition, and interpersonal interactions. The more a person operates or repairs a machine the more experience they gain and the tacit knowledge they carry. This tacit knowledge, therefore, becomes crucial in successful operations for other employees who do not have a similar experience. This was evident in the analysis done in chapter four which shows 41% of the respondents acquire their knowledge through consultation with experienced employees and 53% always need tacit knowledge in their day-to-day operations. All the respondents consult for tacit knowledge from either their senior colleagues or supervisors. These results align with Hadjimichael and Tsoukas's (2019) literature.

6.2.2 Causes of challenges faced in sharing tacit knowledge

Sharing tacit knowledge involves socialization, particularly through close social contacts and experience sharing, according to the literature of Ganguly et al. (2019). The amount of social capital that the interacting people, groups, or organizations possess determines the intensity and effectiveness of social interactions. Sharing tacit information, according to Hadjimichael & Tsoukas (2019), is difficult and time-consuming. It is advantageous to develop settings that encourage the sharing of knowledge. Because it is founded on unique experiences, abilities, and instincts that are challenging to explain and apply to other people. Tacit information is difficult to recognize, define, and express since it is frequently firmly ingrained in people's cognitive and behavioral processes. The authors propose that it may be advantageous to facilitate the exchange of tacit knowledge by developing venues or platforms that support knowledge transfer. The research conducted showed that 88% of the respondents expressed the main challenge is caused by the unavailability of experienced employees when they are required. In addition, when asked what they would change in accessing tacit knowledge, most of the respondents highlighted to the increasing availability of experienced employees.

6.2.3 Validity of the developed system

In accordance the reviewed literature Meyar von Wolff et al., (2019) state that conversational AI bears the potential to assist, solve, or automate tasks in work processes by retrieving and structuring information and providing employees with cognitive relief. Power et al., (2019) further add an AI voice bot can easily provide navigation components, input control, or information components. Equally, the structure process can be built using question-and-answer dialogs to diagnose different situations and add and support decision-making. A voice AI bot can be fast, intuitive, and efficient to use

Using an AI voice bot for sharing tacit knowledge provides consistent information to employees. This can be particularly useful in the repair of locomotives and DMUs which is among the unique operation of Kenya Railways. In addition, it is an area where safety and accuracy are critical. Additionally, an AI voice bot can be available 24/7, allowing employees to access information whenever they need it giving room for those working in shifts or off working hours. Using an AI voice bot to share tacit knowledge in the repair of locomotives could be a useful tool as border training for new employees. Due to its availability, new employees can engage with the voice bot

as many times as required to learn a new concept or seek clarification when repairing the engines. In summary, the voice bot can help increase efficiency, avoid mistakes, save time and ultimately reduce risks of errors and accidents in repairing locomotives.

6.3 Research Limitations

i. The study assumes every employee can access an internet-enabled device to access the voice bot.

ii. The AI voice bot may not be able to convey the nuances and subtleties of certain types of knowledge, such as those that rely heavily on visual or hands-on learning.

iii. The study assumes when the bot escalates a user query the feedback will be obtained as soon as it is required.

iv. The study assumes that all employees are tech survey and are capable of operating a smart device to access the website and engage with it.

Chapter 7: Conclusion and Recommendation

7.1 Conclusion

An efficient method for ensuring business continuity, ongoing orientation, and 24/7 consultation is the employment of an AI voice bot to capture tacit knowledge in the repair of locomotives. However, there are some drawbacks to take into account, such as the absence of nonverbal cues and the limited comprehension of contextual information. The success of an AI voice bot for locomotive repair depends on taking these constraints into account. To make sure the AI voice bot is providing correct and current information, it is crucial to invest in updating it regularly. The performance of the AI speech bot should be monitored, and any problems that emerge should be addressed, using a continuous quality assurance methodology. Quality assurance methods include measuring performance, security, scalability, and functionality of the voice bot. In general, using AI speech bots to capture tacit knowledge in locomotive repair can be a useful tool in a larger training program. However, it should be used in a thoughtful and strategic manner to ensure that users receive a complete and effective experience.

7.2 Recommendation

Based on the potential limitations and considerations discussed above, recommendations for developing an AI voice bot to harness tacit knowledge in the repair of locomotives include:-

i. Conduct a thorough needs assessment: Before developing an AI voice bot training program, it is important to conduct a thorough needs assessment to identify the specific knowledge and skills that trainees need to acquire. This assessment should also consider the limitations and challenges of using an AI voice bot and identify complementary training methods that can be used in conjunction with the AI voice bot.

ii. Develop a robust quality assurance process: To ensure that the AI voice bot is providing accurate and up-to-date information, it is important to develop a robust quality assurance process. This process should include regular updates and testing to ensure that the AI voice bot is functioning.

iii. Evaluate the effectiveness of the AI voice bot: To ensure that the AI voice bot is effective, it is important to evaluate its effectiveness on an ongoing basis. This evaluation should include feedback from users, assessments of knowledge and skill acquisition, and analysis of outcomes.

7.3 Future Work

The development of AI voice bots to harness tacit knowledge in organizations has the potential to revolutionize knowledge transfer and training. As technology continues to advance, there are several areas where future work can be done to further develop the use of AI voice bots in organizations. Here are a few potential areas of focus:

i. Improved Natural Language Processing (NLP): NLP is a key component of AI voice bots, and advancements in this area can improve the accuracy and reliability of AI voice bots in understanding and interpreting human language. Future work could focus on developing more sophisticated NLP algorithms that can better understand context, tone, and other nuances of human language.

ii. Incorporation of Machine Learning (ML): Machine learning can enable AI voice bots to learn and adapt to new information over time. Future work could focus on incorporating ML algorithms into AI voice bots to improve their ability to provide accurate and up-to-date information.

iii. Integration with Augmented Reality (AR): Augmented reality can provide a more immersive training experience by overlaying digital information onto the physical world. Future work could focus on integrating AI voice bots with AR technology to provide users with a more interactive and engaging learning experience.

iv. Personalization: AI voice bots can provide a personalized user experience by adapting to the needs and preferences of individual users. Future work could focus on developing AI voice bots that can provide tailored feedback and support based on the individual needs of each user.

v. Ethical Considerations: As AI voice bots become more prevalent in organizations, it is important to consider the ethical implications of their use. Future work could focus on developing ethical frameworks and guidelines for the use of AI voice bots in training and knowledge transfer.

Overall, the development of AI voice bots to harness tacit knowledge in organizations is an exciting area of research and development. By continuing to explore new technologies and methodologies, organizations can leverage the power of AI to improve knowledge transfer and employee performance.

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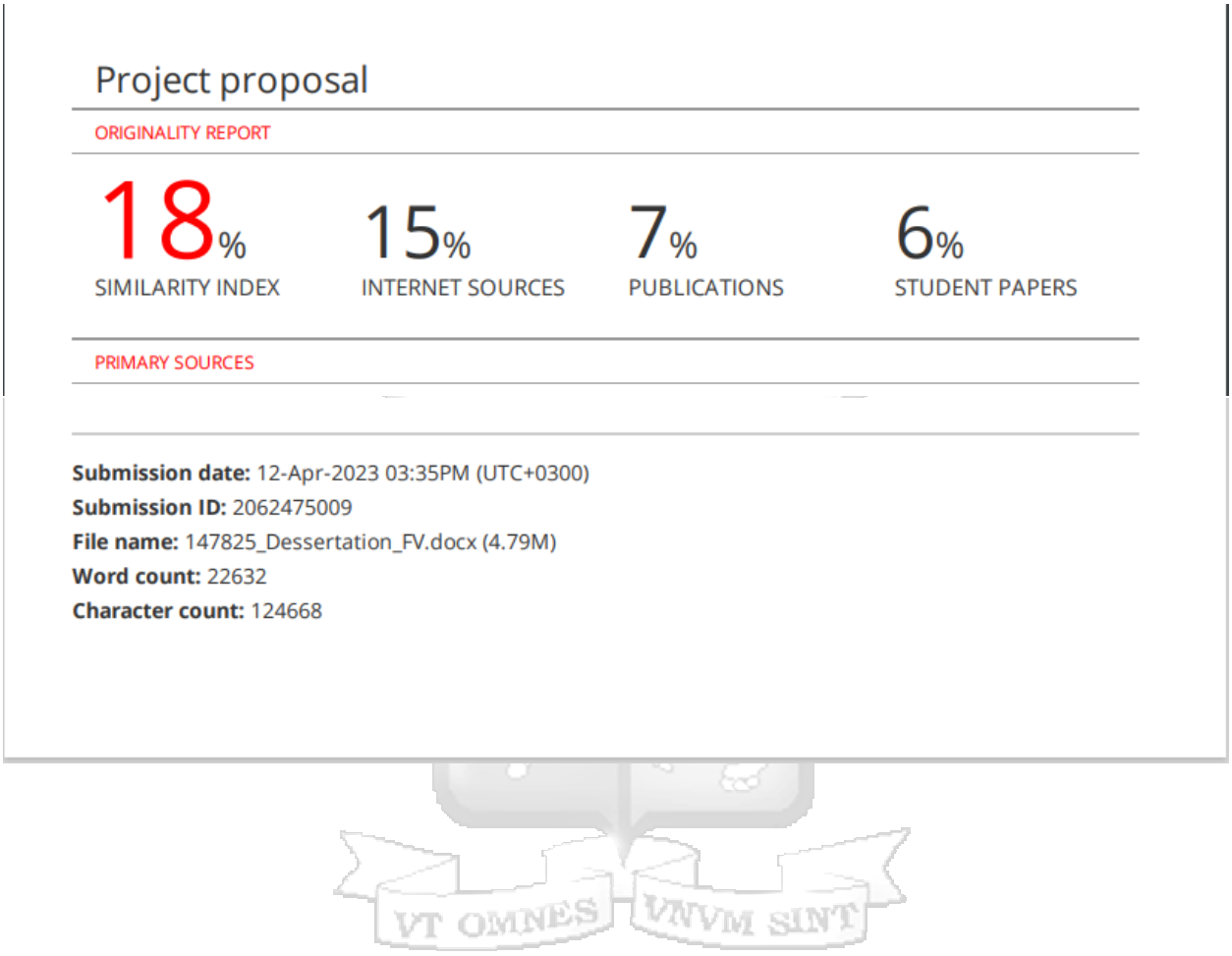
Appendices

Appendix A: Similarity Report



Project proposal

ORIGINALITY REPORT

18%	15%	7%	6%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

Submission date: 12-Apr-2023 03:35PM (UTC+0300)
Submission ID: 2062475009
File name: 147825_Dessertation_FV.docx (4.79M)
Word count: 22632
Character count: 124668

Appendix B: Ethical Clearance Confirmation

Strathmore UNIVERSITY

10th March 2023

Ms Maina Diana,
dianda.maina@strathmore.edu

Dear Ms Maina,

RE: Harnessing Tacit Knowledge to Improve Employee Performance Using AI Voice Detection. A Case of Kenya Railways Corporation

This is to inform you that SU-ISERC has reviewed and **approved** your above **SU- master's** research proposal. Your application reference number is **SU-ISERC1617/23.** The approval period is from **10th March 2023 to 9th March 2024.**

This approval is subject to compliance with the following requirements:

i. Only approved documents including (informed consents, study instruments, MTA) will be used
ii. All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-ISERC.
iii. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-ISERC within 48 hours of notification
iv. Any changes, anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-ISERC within 48 hours
v. Clearance for export of biological specimens must be obtained from relevant institutions.
vi. Submission of a request for renewal of approval at least 60 days prior to expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days upon completion of the study to SU-ISERC.

Prior to commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology, and Innovation (NACOSTI) https://research-portal.nacosti.go.ke/ and obtain other clearances needed.

Yours sincerely,

for: **Dr Ben Ngoye,**
Secretary; SU-ISERC

Cc: Mr Ambrose Rachier,
Chairperson; SU-ISERC

STRATHMORE UNIVERSITY INSTITUTIONAL SCIENTIFIC AND ETHICAL REVIEW COMMITTEE
(SU-ISERC)
10-Mar-2023
P.O BOX 59857-00200
NAIROBI-KENYA

Appendix C :NACOSTI Approval

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: **481209**

Date of Issue: **25/April/2023**

RESEARCH LICENSE

This is to Certify that Miss.. Diana Achieng Maina of Strathmore University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Nairobi on the topic: Harnessing Tacit Knowledge to Improve Employee Performance Using AI Voice Detection. A Case of Kenya Railways Corporation for the period ending : 25/April/2024.

License No: **NACOSTI/P/23/25327**

481209

Applicant Identification Number

Director General
NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

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See overleaf for conditions

Appendix D : Questionnaire

TACIT KNOWLEDGE QUESTIONNAIRE

Dear Respondent,

I am Diana Achieng' Maina a staff of Kenya Railways ICT department. I am currently undertaking my Master's degree at Strathmore University. As part of the requirements for masters I am writing my dissertation project which is developing an Artificial Intelligence (AI)voice bot that will harness tacit knowledge at Kenya Railways. My research targets the Business and Operations Department; operations division - in the Repair of Locomotives and DMU section at the Nairobi Central Workshop. The research entails collecting data through a questionnaire. The purpose of this questionnaire is to collect data on the need and management and effectiveness of tacit knowledge. The data collected will be solely used for the completion of the dissertation project.

CONFIDENTAILITY CLAUSE

Your responses to this survey will be anonymous. Information collected will be handled asconfidential. This information will be used solely for the purpose of the purpose of this research.

CONSENT *

I have read and understood the information provided. I understand my participationis voluntary and I have voluntarily agreed to take part in this study.

Mark only one oval.

- ◯ Agree
- ◯ Disagree

***SECTION A. SOURCE OF TACIT KNOWLEDGE** **Required**

Tacit knowledge is knowledge gained from experience that cannot be found in book, manualor even online. It is in a person's mind and hence you can only get it from consulting that particular person. This section looks at where or from whom tacit knowledge is obtained.

A1. In the Operation division which is your section

Check all that apply.

- ☐ Locomotives section
- ☐ Carriage and wagons section
- ☐ Engineering and Technical Section
- ☐ Plant Maintenance section
- ☐ Production section

A2. What is your role? *

Mark only one oval.

- ◯ Engineering Mechanical Manager
- ◯ Consultant Engineer
- ◯ Principle Engineer
- ◯ Senior Engineer
- ◯ Locomotive coordinator
- ◯ Supervisor
- ◯ Technicians

A3. How long have you been employed? *

Mark only one oval.

- 0 - 5 years
- 5 - 10 years
- More than10 years

A4. Is Induction for new employees Important?

Mark only one oval.

- Yes
- No

A5. Is induction of new employees sufficient to properly handle locomotiverepairs?

Mark only one oval.

- Yes
- No

A6. How do you acquire knowledge you apply when repairing locomotives?*

Check all that apply.

- ☐ Manuals/Procedures
- ☐ Consultation from experienced
- ☐ employeesModification and testing

A7. Which source of knowledge acquired for repair has been most useful? *

Check all that apply.

- ☐ Manuals/Procedures
- ☐ Consultation from experienced
- ☐ employeesModification and testing

A8. Who do you often consult for experience knowledge (Tacit Knowledge)? *

Check all that apply.

- ☐ Engineering Mechanical
- ☐ ManagerConsultant Engineer
- ☐ Principle Engineer
- ☐ Senior Engineer
- ☐ Locomotive coordinator
- ☐ Supervisors
- ☐ Technicians

*SECTION B. CHALLENGES IN SHARING TACIT KNOWLEDGE Required

Tacit knowledge is knowledge gained from experience that cannot be found in a book, manualor even online. It is in a person's mind and hence you can only get it from consulting that particular person.

B1. How frequently do you need tacit knowledge?

Check all that apply.

- [ ] Always
- [ ] Sometimes
- [ ] Never

B2. What are the challenges you face in accessing tacit knowledge?

Check all that apply.

- [ ] Availability of the experienced employees
- [ ] Odd feeling in requesting for the same knowledge more than once

Appendix E: Interview

TACIT KNOWLEDGE INTERVIEW

Dear Respondent,

I am Diana Achieng' Maina a staff of Kenya Railways ICT department. I am currently undertaking my Masters degree at Strathmore University in Computing and Information Systems. As part of the requirements for masters, I am writing my dissertation project which is developing an Artificial Intelligence (AI) voice bot that will harness tacit knowledge at Kenya Railways. My research targets the Business and Operations Department; operations division - in the Repair and Maintenance of Locomotives and DMU section at the Nairobi Central Workshop. The research entails collecting data through an interview. The purpose of this interview is to collect data on the need, management and effectiveness of tacit knowledge. The data collected will be solely used for the completion of the dissertation project.

CONFIDENTAILITY CLAUSE

Your responses to this survey will be anonymous. Information collected will be handled as confidential. This information will be used solely for the purpose of this research.

CONSENT *

I have read and understood the information provided. I understand my participationis voluntary and I have voluntarily agreed to take part in this study.

Mark only one oval.

- ◯ Yes
- ◯ No

SECTION A: TACIT KNOWLEDGE REQUIRED

Tacit knowledge is knowledge gained from experience that cannot be found in books, manualor online. It is in a person's mind and hence you can only get it from consulting that particular person. This section looks at what tacit knowledge is required for a successful repair. This data will be useful in identifying areas employees need guidance from experienced colleagues.

A1. In the Operations division which is your section?

_____

A2. What is your role?

_____

A3. How long have you been employed?

_____

A4. What are the grey areas/challenges you face that require consultation from experienced employees?

_____

SECTION B : FUNCTIONALITY TESTING

This sections collects data on user requirements on specific functions the user requires fromthe system. This will enable system be developed to meet the users' needs and support operations.

B1 On a scale of 1 to 5 where 1 is least required and 5 is most required classify the following functional requirements of the AI VOICE bot.

Check all that apply.

- ☐ The bot is accessible via the website
- ☐ The bot allows users to log in with their credentials
- ☐ Thebot identifies the staff details and history
- ☐ The bot communicates using audio
- ☐ The bot initiates a conversation
- ☐ The bot rephrases the user's input
- ☐ The bot seeks clarification on the feedback it has
- ☐ The bot gives feedback in audio
- ☐ The bot stores the context of a successful conversation
- ☐ The bot seeks support when faced with a question it cannot answer
- ☐ The bot communicates via email when it receives feedback

B2 In a scale of 1 to 5 where 1 is least required and 5 is most required classify the following performance requirements of the AI VOICE bot.

Mark only one oval.

- ◯ Security
- ◯ Scalability
- ◯ Performance
- ◯ Flexibility
- ◯ Availability
- ◯ Usability
- ◯ Reliability

Thank you for your participation