Strathmore UNIVERSITY

SU+ @ Strathmore University Library

Electronic Theses and Dissertations

2024

A Bi-lingual counselling chatbot application for support of gender based violence victims in Kenya.

Mutinda, Sylvia Wairimu
School of Computing and Engineering Sciences
Strathmore University

Recommended Citation

Mutinda, S. W. (2024). *A Bi-lingual counselling chatbot application for support of gender based violence victims in Kenya* [Strathmore University]. https://hdl.handle.net/11071/16563

Follow this and additional works at: https://hdl.handle.net/11071/16563

This work is availed for free and open access by Strathmore University Library.
It has been accepted for digital distribution by an authorized administrator of SU+ @Strathmore University.
For more information, please contact library@strathmore.edu

A Bi-Lingual Counselling Chatbot Application for Support of Gender Based Violence Victims in Kenya

Mutinda Sylvia Wairimu

Submitted in partial fulfilment of the requirements for the Degree of Master of Science in Computing and Information Systems at Strathmore University

School of Computing and Engineering Sciences

Strathmore University

Nairobi, Kenya

April, 2024

This dissertation is available for Library use on the understanding that it is copyright material and that no quotation from the dissertation may be published without proper acknowledgement.

Declaration and Approval

Declaration

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 dissertation contains no material previously published or written by another person except where due reference is made in the dissertation itself.

© No part of this dissertation may be reproduced without the permission of the author and Strathmore University

Sylvia Wairimu Mutinda

Sign: _____

08 April 2024

Approval

The dissertation of Sylvia Wairimu Mutinda was reviewed and approved for examination by the following:

Sign: _____ _____

Date: **08 April 2024**

Dr. Henry Muchiri,

Lecturer,

School of Computing & Engineering Sciences,

Strathmore University.

Abstract

Gender-based violence (GBV) remains one of the highest prevailing human rights violations globally, surpassing national, social, and economic boundaries. However, due to its nature, it is masked within a culture of silence and causes detrimental effects on the dignity, health, autonomy, and security of its victims. The prevalence of GBV is fuelled by cultural nuances and beliefs that justify and promote its acceptability. The stigma surrounding GBV in addition to fear of the consequences of disclosure deter victims from seeking help. Additionally, the resources available for addressing GBV such as legal frameworks and recovery centres are limited.

Technological approaches have been established to tackle GBV as intermediate and supplementary support for victims as part of UN-SDG 5. Conversational Agents such as Chomi, ChatPal, and Namubot have been developed for counselling of GBV victims who struggle with disclosing their predicament to humans. The existing chatbots, however, are not a fit for Kenyan victims because they utilize languages such as Swedish, Finnish, Isizulu, Setswana and Isixhosa in addition to incorporating referral services specific to their regions. This research addressed this gap by developing a chatbot application suitable for the Kenyan region for counselling of GBV victims using both Kiswahili and English, the languages predominantly used in the country, in addition to including contacts to referral services within the country.

The methodology utilized involved the development of a chatbot application based on Rasa open source AI framework by training a model using a pre-processed counselling dataset.The performance of the model was evaluated using NLU confidence score to determine the model's certainty in its intent identification and a confusion matrix was generated which with 80% and 20% training and testing data split resulted in 100% classification threshold accuracy. Python's Fuzzy Matching Token Set Ratio score was also used to determine the response which best matches the input with results indicating satisfactory performance of the model ranging between 63% and 92% for GBV queries input. The developed model was then integrated into a web application as the user interface for user access and interaction with the model hence achieving the research objective of developing a chatbot application to conduct counselling for GBV victims in Kenya using English and Kiswahili languages .

Keywords: Gender-based Violence, stigma, chatbot, Rasa open source, NLU Confidence Score, Fuzzy Matching Token Set Ratio score

Table of Contents

Declaration and Approval ii

Abstract iii

Table of Contents iv

List of Figures vii

List of Tables ix

List of Abbreviations/Acronyms x

Definition of Terms xi

Acknowledgments xiii

Chapter 1: Introduction 1

1.1 Background to the study 1

1.2 Problem Statement 3

1.3 Research Objectives 4

1.3.1 Main Objective 4

1.3.2 Specific Objectives 4

1.4 Research Questions 4

1.5 Justification and Significance of the study 4

1.6 Scope and Limitations of the study 6

1.6.1 Scope 6

1.6.2 Limitations and Delimitations of the Study 7

Chapter 2: Literature Review 8

2.1 Overview 8

2.2 Importance of Resolving Gender-Based Violence 9

2.2.1 The Gender-Based Violence Case 10

2.2.2 The Kenyan Language Context 12

2.3 Response to Gender-Based Violence 13

2.3.1 Traditional Response to Gender-Based Violence 13

2.3.2 Technological Response to Gender-Based Violence 15

2.4 Related Applications 18

2.4.1 Chomi- Multilingual Chatbot for GBV Victims in South Africa 18

2.4.2 ChatPal: Multilingual Digital Mental Health and Wellbeing Chatbot 19

2.4.3 Namubot: A Conversational Agent for Sexual Assault Survivors 21

2.5 Conceptual Framework 22
Chapter 3: Methodology 25
3.1 Overview 25
3.2 Experimental Research Design 25
3.3 The Chatbot Application Development 25
3.3.2 Developing a machine learning model for GBV counselling in English and Kiswahili 26
3.3.6 Integrating the Developed Model into a Web Application 28
3.4 Application of Iterative Methods in the Chatbot Development 29
3.5 Validity and Reliability of the Study 30
3.6 Ethical Considerations 31
Chapter 4: System Design & Architecture 33
4.1 Introduction 33
4.2 Requirements Analysis 33
4.2.1 Functional Requirements: 33
4.2.2 Non-Functional Requirements: 34
4.3 Chatbot Application Design 34
4.3.1 Chatbot Application Architecture 34
4.3.2 Use Case Diagram 35
4.3.3 Sequence Diagram 38
4.3.4 Chatbot Application Wireframe 40
Chapter 5: Chatbot Application Implementation and Testing 42
5.1 Introduction 42
5.2 The Chatbot Application Components 42
5.2.1 Rasa AI framework 42
5.2.2 The Web application 44
5.3 Implementation of the Chatbot Application 45
5.3.1 The Development Environment 46
5.3.2 Data Pre-processing and Multilingual Integration 46
5.3.3 Model Training and Evaluation 54
5.3.4 Model Training using the Pre-processed Data Files 61
5.3.5 Testing of the Chatbot Application Model with GBV Queries 62
5.3.6 Deployment of the chatbot model 72
Chapter 6: Discussions 77
6.1 Introduction 77
6.2 Discussion of Results 77
6.2.1 Accuracy of the Chatbot Application Response Generation 77

6.2.2 Attainment of Set Objectives 80
6.2.3 Advantages of the Developed Chatbot Application to the Related Applications 81
6.2.4 Shortfalls and Challenges of the study 82
Chapter 7 Conclusion and Recommendations 84
7.1 Conclusions 84
7.2 Recommendations 85
References 86
Appendices 92
Appendix 1: The Chatbot Application Development Sprints 92
Appendix 2: Similarity Report 94
Appendix 3: Chatbot Application Source Code 97
0.1 Pre-processing for Domain 97
0.2 Pre-processing for NLU 98
0.3 Pre-processing for Rules 99
0.4 Pre-processing for Stories 100
0.5 Conversion for Domain 101
0.6 Conversion for NLU 104
0.7 Conversion for Rules 108
0.8 Conversion for Stories 108
0.9 Custom Action for Fuzzy Matching and NLU Confidence Scores 111
0.10 Endpoints File 111
0.11 Configuration File 112
Appendix 4: Ethical Approval Letter 113

List of Figures

Figure 2.1	Conceptual Framework of the Study	24
Figure 4.1	Chatbot Application Architecture	35
Figure 4.2	Chatbot Application Use Case Diagram	37
Figure 4.3	Chatbot Application Sequence Diagram	39
Figure 4.4	Chatbot Application Home Page with Chatbot Interaction Section	40
Figure 4.5	Chatbot Application Referral Services Page	41
Figure 4.6	Chatbot Application Grounding Exercises Page	41
Figure 5.1	Web Application Chatbot Section	45
Figure 5.2	NLU file content format	52
Figure 5.3	Domain File Content Format	53
Figure 5.4	Rules File Content Format	53
Figure 5.5:	Stories File Content Format	54
Figure 5.6	“rasa -h” Command Output	57
Figure 5.7	Rasa Project Files Format	58
Figure 5.8	Greeting Interaction in English	59
Figure 5.9	NLU File in Kiswahili	59
Figure 5.10	Domain File in Kiswahili	60
Figure 5.11	Training of a Chatbot Model	60
Figure 5.12	Greeting Interaction in English	61
Figure 5.13	Interactive Session with the Trained Model	62
Figure 5.14	Generated Response Snippet 1	63
Figure 5.15	Generated Response Snippet 2	63
Figure 5.16	Custom Action Source Code	66
Figure 5.17	Running the Actions Server	70
Figure 5.18	Conversation in English with 76% NLU confidence and 92% Fuzzy Matching	71
Figure 5.19	Conversation in English with 82% NLU confidence and 63% Fuzzy Matching	71
Figure 5.20:	Conversation in Kiswahili with 89% NLU confidence and 67% Fuzzy Matching	72

Figure 5.21	Conversation in Kiswahili with 99% NLU confidence and 76% Fuzzy Matching	72
Figure 5.22	The Specified Endpoints	73
Figure 5.23	Rasa Server Feedback as Up and Running	73
Figure 5.24	Rasa Actions Server Feedback as Up and Running	73
Figure 5.24	Interaction with the Chatbot Model on the Web Application	76
Figure 6.1	Generated NLU Classification Confusion Matrix	79

List of Tables

Table 3.1	The Dataset Columns	27
Table 5.1	Single Multilingual compared to Multiple Language-Specific Model	49
Table 5.2	Miniconda Packages for Chatbot Application Development	70
Table 5.3	Response Enhancement Summary	67

List of Abbreviations/Acronyms

AI	Artificial Intelligence
API	Application Programming Interface
CA	Conversational Agents
CSS	Cascading Style Sheets
DHS	Demographic Health Survey
GBV	Gender-Based Violence
HTML	Hyper Text Mark-up Language
ICF	International Classification of Functioning, Disability and Health
IRC	International Rescue Committee
KDHS	Kenya Demographic Health Survey
KNBS	Kenya National Bureau of Statistics
SDK	Software Development Kit
UN	United Nations
UNFP	United Nations Population Fund
UNHCR	United Nations High Commission for Refugees
UNSDG	United Nations Sustainable Development Goals
WHO	World Health Organization

VT OMNES VNVM SINT

Definition of Terms

Artificial Intelligence	Is the intelligence exhibited by machines to display them as rational agents which will perceive their surroundings and make decisions (Patil & Rasave, 2021).
Chatbot	A chatbot is a service, powered by rules of Artificial Intelligence (AI) that citizens can interact via a chat interface (Patil & Rasave, 2021).
Conversational Agent	Are agents that interact with users via written or spoken natural language and accept as input natural language as speech, text, or vide and are required to process the input and provide relevant advice or feedback in a form of text or speech or by manipulating a physical or a virtual body (Allouch, Azaria, & Azoulay, 2021).
Counselling	This is a process focusing on immediate psychosocial needs that aims to provide survivors with tools to help them address those needs. It focuses on the development of emotional coping strategies, social skills and communication skills, as well as decision making and problem solving (UNFPA, 2020).
Gender Based Violence	Harmful acts of abuse perpetrated against a person's will and rooted in a system of unequal power between women and men (IRC, 2022).
Natural Language Processing	Is a tract of Artificial Intelligence and Linguistics devoted to make computers understand the statements or words written in human languages (Khurana, Koli, Khatter, & Singh, 2022).
Psychosocial support and mental health	This term refers to any form of local or external support that protects and promotes the psychosocial well-being of individuals and/or prevents, or treats mental conditions (UNFPA, 2020).

Psychotherapy	This is the process of treating psychological problems, such as depression, anxiety or post-traumatic stress. Based on the approach adopted by the psychologist, different verbal and psychological techniques can be used (UNFPA, 2020).
Sentiment Analysis	Is the process of gathering and analysing people's opinions, thoughts, and impressions regarding various topics, products, subjects, and services (Wankhade, Rao, & Kulkarni, 2022).

Acknowledgments

I acknowledge the grace of God throughout this research and thank Him for the strength, insight, wisdom, favour and every kind of support for every aspect of this dissertation. All glory goes to Him for the successful completion of this dissertation. I am deeply grateful to my supervisor, Dr. Henry Muchiri, for his insightful guidance and understanding nature throughout the course of this dissertation. His expertise significantly enriched this dissertation and aided in shaping its direction to the success story it is. My sincere appreciation to my family, friends, and classmates for their continual motivation and support throughout this dissertation compilation. I could not have done this without their unwavering support and relentless encouragement to push through.

Chapter 1: Introduction

1.1 Background to the study

IRC (2022) defines GBV as "harmful acts of abuse perpetrated against a person's will and rooted in a system of unequal power between women and men." GBV impacts individuals across various socio-economic backgrounds and geographical regions. GBV is a pandemic whose drawbacks have a universal reach and it ails the entire globe. It encompasses different forms of violence, including physical, sexual, emotional, and economic abuse, with women and girls being the primary targets. GBV is rooted in power imbalances, cultural norms, and gender inequality, perpetuating discrimination and violence against women.

Technology is proposed, even by UNSDG-5, in resolving GBV because of its vast attributes (UN, 2023). These include the ability to provide victims with access to the service providers and essential resources critical to them equipping them with technologically enabled safety devices and assisting victims with the development of safety plans. Additionally, technology can be used for evidence collection and empowerment of victims by ensuring they maintain social engagement through social media interactions and involvement in online support groups hence reducing the feeling of seclusion (Al-Alosi, 2020). Concurrently, technology is of the essence in dealing with GBV.

The explosive progress in technology and its applications brought about the development of conversational agents (CAs) for the enhancement of seamless human-machine communication to be even more effortless and steadily more natural. The CAs are suitable for the GBV context because they are perceived by users as lacking the element of judgment and prejudice hence reducing the burden of disclosure experienced by GBV victims. In addition, they have privacy features that would make individuals feel confident about sharing sensitive information. Concurrently, user experience can be enhanced by improvement of the features to suit the needs of the target group. Furthermore, conversational agents have multiple means of deployment through web pages, desktop applications, and mobile applications in addition to other interfaces (Griffing, 2023). Considering this interoperability and the aforementioned attributes, they are recommended for the management of mental health and they leverage psychological expertise to foster human-like conversation for counselling.

Accordingly, conversational agents such as Chomi, ChatPal, and Namubot have been developed for the support of GBV victims in their regions. Both Chomi and ChatPal chatbots

are multilingual with English as one of the languages in addition to Isizulu in Chomi to meet the South African context while ChatPal incorporates Swedish, Finnish, and Scottish Gaelic for its target regions (Potts, et al., 2023; Shout It Now, 2021). They also contain region-specific information such as the national legal framework, safety planning elements and response services. Therefore, to support GBV victims in Kenya, this study has developed a conversational agent that is suitable for the country and caters to the specific needs of Kenyan victims in terms of the languages that the conversational agent uses, appropriate referrals to response services and rescue centres available in Kenya, in addition to region-specific safety planning content to ensure relevance and effectiveness to a Kenyan user.

1.2 Problem Statement

Victims of GBV struggle with disclosing their experiences to Human professionals due to fear of unwanted consequences, the fear of bias, and the stigma of being judged (Neetu, Charlotte, Mwangi, Neha, & McGovern, 2021). Additionally, the victims experience difficulty in accessing physical support services at particular times such as at night. Furthermore, counselling and psychotherapy services are few in addition to the sessions in Kenya costing Kshs2000 an hour at a minimum which is relatively expensive (Terembe, 2022; Inkster, Sarda, & Subramanian, 2018). There is also limited capacity of recovery centres where GBV victims can access the support they require with Kenya only having 11 GVRC branches countrywide (GVRC, 2023).

There are existing chatbots for counselling such as Chomi, Chatpal and Namubot but they do not cater to the needs of GBV victims in Kenya. Aside from English, Chomi has Isizulu and is working on Setswana and Isixhosa languages while ChatPal has Swedish, Scottish Gaelic and Finnish Gaelic language demostrating that langauge is key in enhancing effective support for GBV victims (Aldkheel & Zhou, 2023; Potts, et al., 2023; Shout It Now, 2021). With the current chatbots, Kenyan GBV victims would only have the English option which alienates those who may not be conversant with the language hence presenting a language barrier that would deter people in Kenya from using the current chatbots. Furthermore, the existing chatbots lack referrals available and content relevant to Kenya because they incorporate tailor-made support and safety planning details for their locations, incorporate the legal frameworks in their countries and referrals to centres and proffessionals available in their regions. Such resources would not be applicable to a Kenyan victim hence hindering them from accessing the support they need.

1.3 Research Objectives

1.3.1 Main Objective

To develop a bi-lingual chatbot application for counselling of GBV victims in Kenya using English and Kiswahili languages.

1.3.2 Specific Objectives

1. To analyze the challenges experienced by GBV victims in Kenya.
2. To analyze the weaknesses of the existing interventions to GBV.
3. To develop a chatbot for GBV counselling in English and Kiswahili.
4. To validate the developed chatbot.

1.4 Research Questions

1. What are the challenges experienced by GBV victims in Kenya?
2. What are the weaknesses of the existing technological interventions for GBV?
3. How will a chatbot with the capability to conduct GBV counselling in English and Kiswahili be developed?
4. How will the developed chatbot be validated?

1.5 Justification and Significance of the study

This study is of the essence because it develops a conversational agent that provides a practical solution to the persistent problem of Gender Based Violence experienced in Kenya. It enables GBV victims to access immediate and long-term emotional support from the counselling service provided by the developed chatbot. Furthermore, the study demonstrates the significant contribution of utilizing technology for the alleviation of societal problems and the common good.

The study is aimed at making a lasting and meaningful impact in the improvement of GBV victim's lives in Kenya. The modelling of the chatbot addresses a pressing and persistent detrimental implication of the prevalence of GBV in the Kenyan community. GBV cases have psychological, physical, social, and economic among other negative impacts and hence the emotional support of the victims using the developed chatbot has the potential to guide the victims towards the path of recovery.

Additionally, SafeCouse includes the Kenyan context localized support because the predominant language used by people in Kenya involves natural code-switching between English and Kiswahili, which is the focus of this conversational agent. The cultural context of Kenya including the linguistic tendencies of its people is incorporated in the development of the chatbot application. Since the code-switch is utilized by Kenyans with the aim of effective communication, this bi-lingual conversational agent improves the effectiveness of the support offered to the GBV victims in Kenya. It also caters to the victims who do not have mastery of English or Kiswahili but use snippets of both languages to communicate hence being more accommodating and inclusive of a wider reach of people in Kenya.

Concurrently, there are limited resources available for combating GBV in Kenya. Further, the available resources are not accessible to all regions. In addition, there are hefty cost implications for the available resources such as counselling for those people unable to access the free services offered by the Government. Such constraints discourage victims from seeking assistance and deny them the opportunity to proceed to the path of healing. This chatbot, therefore, helps bridge the gap of limited resources by providing a resource that is readily available for the victims to access emotional support, resources, and guidance. Consequently, the chatbot will benefit large numbers of victims across the country.

Furthermore, GBV victims suffer from the stigma of disclosing their situations. In addition, talking to an individual may bring about the question of trust or feeling that there is prejudice or a lack of partiality. The victims may also be afraid that the perpetrators will find out that they are seeking help and fear facing the consequences of this disclosure. The developed chatbot provides anonymity and privacy in addition to eliminating the fear of exposure or being judged while seeking support.

The developed chatbot also makes significant contributions to awareness and advocacy regarding GBV. This is because it is a tool that acknowledges that GBV is a critical issue that requires it to be researched and addressed so that its consequences are minimized. Utilizing technology in handling GBV potentially provides further insight into human-centered AI as well as the GBV issue hence the data collected is useful for data-driven policy making and further advocacy in the future.

1.6 Scope and Limitations of the study

1.6.1 Scope

The study involves the technical development of a chatbot. The development of the chatbot fundamentally utilized an existing open-source machine-learning framework called Rasa. The development of the Machine learning model involved using the two major modules of the Rasa framework which are the Rasa Natural Language Understanding (NLU) section for the comprehension of the user messages and the Rasa Core module for dialogue management.

The technical development of the machine learning model included subjecting the model to a counselling dataset in English and Kiswahili. This created a bi-lingual chatbot that can accommodate input from a user in both English and Kiswahili as people in Kenya do and, subsequently, generate responses similarly. The developed chatbot having capability to converse in both English and Kiswahili enhances the linguistic and cultural aspect of the study because it facilitates natural and comfortable communication for Kenyans. The developed and tested model is then deployed on a web page which provides a platform for users to interact with the chatbot.

The ethical framework of the developed chatbot ensures the integration of adherence to ethical stipulations related to counselling interactions by following psychosocial counselling guidelines provided for services which supplement and act as an intermediary service for victims not able to immediately access or afford professional psychotherapy sessions. Concurrently, the model ensure that the privacy of the victim and their disclosure is upheld and that the appropriate responses are generated for sensitive information shared.

The model was tested by interacting with the model through the Rasa shell environment using GBV related queries to check for accuracy of the responses. The creation of this chatbot is, however, not inclusive of creating a conversational agent to provide professional psychological counselling hence its development is not a replacement for human counsellors but rather avails a tool for emotional support of the GBV victims and reduces the burden of disclosure to humans who may be perceived to be judgemental. Additionally, the study focused on a localized approach that limited itself within the Kenyan context. The research, however, does recognize that even with this localization and cultural sensitivity to the Kenyan context, individuals also have personal interpretations of concepts, cultural cues, and languages and this presents an additional variability.

Concurrently, the chatbot has been developed and evaluated within the constraints of time, technology, and resource availability. It is also confined to the Kenyan region hence focusing on needs of GBV victims within the country. Furthermore, despite the multilingual state of Kenya where there are more than 43 dialects spoken, the scope of this study only engages English and Kiswahili for the development of the conversational agent's primary language interface. In addition, the chatbot application will be limited to use by individuals with devices such as smart phones and computers which have a browser for accessing the web application. These are the boundaries within which the developed chatbot is confined.

1.6.2 Limitations and Delimitations of the Study

The use of English and Kiswahili languages has the potential to be affected by individual language variabilities and cultural nuances whereby different people have variations in their use and interpretation of language. These individual distinctions can affect the language model comprehension and response accuracy when dealing with diverse users. Concurrently, the technological capabilities of the model to understand the complexities of emotional expressions of humans are dependent on the capacity of the NLP model and the proficiency of the framework utilized hence the accuracy and appropriateness of the responses generated by the chatbot are highly reliant on the technology utilized. In addition, the privacy and security of the information shared during interactions with the chatbot cannot be completely guaranteed despite incorporating the outlined ethical stipulations hence still posing some risks.

For the delimitations, the geographical scope of the study focuses on GBV victims within Kenya. The unique linguistic nature of the Kenyan interactions is considered in addition to some of the specific cultural factors. In addition, the chatbot offers non-professional counselling hence is not a replacement for the psychological counselling offered professionally and is not a substitution for professionally trained counsellors. The counselling offered is also focused on GBV hence broader counselling resources and topics are outside the scope. Further, the Rasa framework selected for development to cater to the GBV context only utilizes this model and no other available frameworks. The study does not also delve deep to establish the intricate details of the functionalities of the framework selected. The study is also focused on primarily chatbot interactions housed in a specific platform, the web application, but does not extend to potential variations across platforms and devices hence affecting user experience.

Chapter 2: Literature Review

2.1 Overview

To understand the research problem and adequately investigate it, a review of the subject matter and the existing challenges experienced by Gender-Based Violence victims was conducted as part of the theoretical framework of this study. The impact of GBV is also included in the study to understand the prevalent issues and challenges related to gender-based violence and how they impact the well-being of individuals. Publications by researchers and accredited scholars on the GBV subject matter have been examined. This comprises the current state of affairs and interventions already employed to alleviate GBV. The application of technology as researched by scholars and researchers across the globe on addressing GBV is included in this theoretical framework. The crowning of this literature review then provides a representation of the study in the form of a conceptual framework as an aggregate of the context.

The initial step of the chatbot application development was to conduct an analysis of the plight of GBV victims around the world by conducting a review of the literature published on the topic of GBV. This included discussing the existing interventions globally for the support of GBV victims in addition to their critical evaluation to determine their fitness for the support of GBV victims in Kenya. Furthermore, this literature review involved examining similar studies that outline the requirements for modelling a mental health chatbot suitable for the Gender-Based Violence context. Accordingly, the study by Aldkheel & Zhou (2023) which outlines meta requirements and design principles when developing a chatbot application for the support of GBV victims had its findings incorporated into the development of this application.

Therefore, the literature review was conducted as a feasibility study and requirements planning for the identification of the prerequisites in the building of the chatbot application. Material on the GBV case in Kenya was evaluated to identify the particular needs of GBV victims in the Kenyan population. This focused on how best to design the chatbot application considering inclusivity, acceptability, and accessibility by ensuring that Kenyan users feel that they are having an organic conversation in their natural linguistic tendencies. Recommendations from previous research on design principles for developing conversational agents aimed at counselling GBV victims were considered as output of objective 1 and 2 which were fed as input for the achievement of the third objective. Objectives 1 and 2 were achieved in this of the dissertation.

2.2 Importance of Resolving Gender-Based Violence

The term "Gender-Based Violence" is often used interchangeably with "Domestic Violence" although they have a significant difference that demands clarification especially due to the development of policies in response to the menace. Domestic Violence is a form of Gender Based Violence and it is established to be the most widespread form of GBV. Subsequently, GBV is inclusive of Domestic Violence and Violence against women and girls (Wilson Center, 2023; WHO, 2022). The distinction is that GBV comprises any kind of violence that is aimed at a person based on their sex, is usually rooted in harmful norms and abuses of power, and is not restricted to women but also men and other people who do not conform to any gender (Wilson Center, 2023).

On the other hand, domestic violence is contextually determined to involve Intimate Partner Violence because the individuals have an intimate relationship, even if same-sex intimate relationships (WHO, 2022). In the case of domestic violence, both men and women can be victims or perpetrators. The forms of GBV which focus on the female gender are “Violence Against Women and Girls” (VAWG) and Femicide which is the most severe form of GBV because it is the murder of a woman because of her gender (Wilson Center, 2023). In this paper, the broader term, Gender-Based Violence, is utilized.

According to the World Health Organization WHO (2021), Worldwide, 1 in 3 (30%) women have experienced physical and/or sexual violence in their lifetime. 38% of all murders of women are committed by intimate partners. Globally, one third (27%) of women aged 15-49 years who have been in a relationship report that they have been subjected to some form of physical and/or sexual violence by their intimate partner. The United Nations Population Fund (UNFPA) states that globally, around 137 women are killed by a family member every day. An estimated 200 million women have undergone female genital mutilation (FGM) worldwide. The United Nations Entity for Gender Equality and the Empowerment of Women (UN Women) reports that only 52% of women married or in a union freely make decisions about their sexual relations, contraceptive use, and healthcare.

The UN and its member nations are at the forefront of addressing GBV by including this agenda as part of their key growth objectives. The United Nations Sustainable Development Goal (UN SDG) number 5 is the achievement of gender equality and the empowerment of all women and girls. The UN defines specific objectives on the key performance measures that would indicate the attainment of this goal. The UN indicates that women's rights are curtailed in both private

and public domains through discriminatory laws and cultures. The prevalence of GBV and the need to address it as a serious concern informed the UN's decision to include this SDG as one among the 17 SDGs. Combating the impact of GBV also aligns with other relevant UNSDGs, such as SDG 3 (Good Health and Well-being), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 16 (Peace, Justice, and Strong Institutions), as it addresses health, technological innovation, and access to justice for survivors.

Consequently, Kenya aligns with UNSDG 5 by having goals, policies, and strategies of its own in curbing GBV. Kenya demonstrated this by having Gender Mainstreaming in the Kenyan National Action Plan 2020-2024 (KNAP II) as part of strategies for the achievement of Vision 2030 by implementing different strategies (Government of Kenya, 2020). These include using interventions such as the establishment of Sexual and Gender-Based Violence Response Centres (SGVRC).

2.2.1 The Gender-Based Violence Case

Victims of GBV experience a self-disclosure burden due to cultural norms because admission that an individual has been through GBV especially when the perpetrator is of close relation still draws extensive stigmatization (Neetu, Charlotte, Mwangi, Neha, & McGovern, 2021). In most cases, the victims hesitate or completely refrain from divulging information about the encounter to the extent of denying that they have undergone such dehumanizing experiences (Park & Lee, 2020). Fear of the consequences of disclosure, resource inaccessibility, and stigma are the most significant reasons why GBV victims are afraid of seeking assistance about their situation (Potts, et al., 2023). Furthermore, rural areas in Kenya have fewer support services such as safe houses and GBV Specialized care facilities in addition to being more vulnerable to traditional practices and cultural beliefs, hence the access to information and assistance is increasingly limited.

The Covid-19 pandemic raised an alarm about the significant extent and impact of Gender-Based Violence. A study on the GBV issue in Kenya during COVID-19 indicates that pandemics and the restrictions imposed by governments to control the pandemic exacerbate the existing inequalities and amplify the exposure of individuals to GBV (Neetu, Charlotte, Mwangi, Neha, & McGovern, 2021). The research establishes that it is during these times that there is heightened inaccessibility to GBV services hence leading to the multiplication of the already adverse effects of the menace because even the available resources are redirected to the emergency services tackling the pandemic at hand such as during Covid-19 (Neetu,

Charlotte, Mwangi, Neha, & McGovern, 2021). The study suggests that as much as the Pandemic puts strain on the resources allocated to GBV response, the existing social protection and health systems are already weak hence what the pandemics do is expose the situation.

Even before Covid-19 when GBV prevalence rose at an alarming rate, Kenya was already experiencing high numbers of GBV cases. According to the Kenya Demographic Health Survey of 2015, the percentage of women reporting having experienced any of the different forms of GBV was recorded as 40.7% (KNBS and DHS Program, 2015). As much as studies indicate that there have been improvements made in alleviating GBV in Kenya as determined by declining numbers of GBV cases, they also acknowledge that the recorded progress is lagging (Neetu, Charlotte, Mwangi, Neha, & McGovern, 2021). Furthermore, studies show that some forms of GBV are decreasing while others are becoming more rampant. Kenya Demographic Health Surveys between 2008 and 2014 examined establishes that between 2008 and 2014, physical violence incidences recorded considering all age groups rose from 38.5% to 44.8% while in the same period, sexual violence prevalence dropped from 20.6% to 14.1%.

The Gender Violence Recovery Centre (GVRC) in Kenya reported that in 2020 they received approximately 14,000 cases of GBV, an increase from previous years. Nairobi accounted for the highest number of reported cases (Aldkheel & Zhou, 2023). In 2022, the KDHS compiled a report on the prevalence of GBV (KNBS and ICF, 2023). This report indicates that in 2022, the percentage of women from the age of 15, in Kenya, who have experienced physical violence is 34%. Further, men from age 15 who have experienced physical violence, considering the same duration, are at 27% (KNBS and ICF, 2023). Although there is a noted reduction between the KDHS 2014 report and the KDHS 2023 report, it is evident that the measures put in place to curtail GBV are still insufficient because the statistics infer significant percentages of GBV cases.

As per the statistics derived and the nature of GBV, it remains a complicated and prevalent issue yet with significantly detrimental effects on all affected parties including the victims, survivors, communities, and countries, and subsequently escalating to be a global concern (Aldkheel & Zhou, 2023). The quality of life of victims, either the survivors or potential victims, is drastically affected by GBV because their physical, mental, and emotional well-being is impacted. Subsequently, GBV results in social, economic, and health costs for both individuals and the larger society (Aldkheel & Zhou, 2023). There is a myriad of factors to which GBV is attributed. These enablers include social and cultural convictions, gaps in law

enforcement that present vulnerabilities in the protection of victims, economic constraints, alcohol and substance abuse in addition to psychological issues are some of the contributors to the problem (Aldkheel & Zhou, 2023). The list is however not exhaustive because of the wide range of constituents to the GBV issue.

Research shows that addressing GBV in Kenya is tremendously influenced by cultural convictions, acceptability, and justifications which curtail the progress made in reducing the prevalence of GBV (Neetu, Charlotte, Mwangi, Neha, & McGovern, 2021). This can be demonstrated by KDHS results between a similar period whose findings established that in Kenya, 43.7% of men and 52.6% of women in 2008 reported that they agreed that under certain conditions, wife beating is justified and admissible which compared with 2014, the perspective had not changed significantly since the same convictions were reported by 36.2% male and 41.8% female participants in the study. Other traditional practices in Kenya such as Female Genital Mutilation (FGM) and Early or Child Marriages aggravate the GBV situation in the country (Neetu, Charlotte, Mwangi, Neha, & McGovern, 2021).

2.2.2 The Kenyan Language Context

Kenya is recognized as a multilingual society. The country has more than 43 languages and dialects drawn from its 43 officially recognized ethnic groups as of 2017 when the Makonde tribe was gazetted as a tribe in Kenya (UNHCR, 2017). Aside from these indigenous languages, Kenya adopted English out of the influence of its British Colonizers and it is the official language of the nation (Bore, 2019). Further, Kiswahili was also declared as Kenya's other official language. Subsequently, both languages are part of the education curriculum and hence are taught through the course of the education system from Kindergarten to primary to Secondary schools as mandatory and examinable subjects (Bore, 2019). These are the two languages utilized for academic, economic, and social interactions. As much as both languages are used as the Languages of Instruction (LOI), not all Kenyans have fluency in English and Kiswahili. Out of this, the Kenyan context is that, in conversation, people in the country constantly and naturally switch between English and Kiswahili except for official purposes where individuals strive to be consistent with either English or Kiswahili.

Kenya having English and Kiswahili as the recognized official languages infer that in the event of seeking assistance, Kenyans would use either of the 2 languages to explain themselves and to effectively attain their communication goals (Wawire, 2017). Addressing the challenges of persistent significant numbers of GBV cases in Kenya necessitates a comprehensive approach

which accommodate the linguistic nature of Kenyans (Neetu, Charlotte, Mwangi, Neha, & McGovern, 2021). The developed conversational agent focuses on providing care in the form of counselling services which contributes to enhancing the support system for GBV survivors in Kenya. The chatbot significantly improves accessibility, subsequently empowering survivors and improving their extensive well-being. Some conversational agents have been developed in different parts of the world but they predominantly use one language, especially the English language in addition to other languages used within their regions to ensure effectiveness of the interaction.

Therefore, this conversational agent which leverages the extensive potential benefits of utilizing Kiswahili and English for addressing GBV in Kenya by offering both languages' counselling services allow users to use either of the languages for the input and get a response in a similar form for confortable interaction when seeking help. This creates a wider reach for Kenyans and the chatbot is embraced more because of the use of a language the people are familiar with hence ensuring the interaction feels natural to them (Wawire, 2017). Additionally, it increases the chances that more people will utilize the developed conversational agent because it provides inclusivity, even for those individuals who lack proficiency in the English language as is the case for most people in the Kenyan Rural and Semi-urban areas.

2.3 Response to Gender-Based Violence

2.3.1 Traditional Response to Gender-Based Violence

There are measures currently put in place for GBV response and prevention. In Kenya, varied forms of GBV exist. These comprise cultural practices including Female Genital Mutilation (FGM), widow inheritance, and child marriages (Okech, 2019) (Kwamboka, 2022). Sexual abuse and domestic violence are also prevalent GBV cases in the country. Statistics show that women in Kenya are disproportionally more affected by GBV than men, as is the case with most countries in Africa (Kwamboka, 2022). The periodic Kenya Demographic and Health Survey (KDHS) findings indicate the extensiveness at 40% of women having undergone sexual or physical intimate partner abuse in the course of their lives, child marriages at 23% prevalence, and FGM recording 21% widespread presence (Kwamboka, 2022). According to Kenyan regulations, subjecting an individual to GBV is a gross contravention of their elemental human rights in addition to compromising their self-esteem and worth which subsequently results in suicidal attempts, isolation, self-harm, and depression (Kwamboka, 2022).

Accordingly, an integrated approach is crucial for addressing GBV cases. Urgent and immediate care and support are emphasized as a first measure in dealing with a victim of GBV (Kwamboka, 2022). This measure is aimed at helping the victim handle the ordeal effectively at the initial instance. Concurrently, counselling is recommended at this initial stage in addition to medical attention to tackle the health implications of the event (Kwamboka, 2022). Furthermore, some cases demand the physical isolation of the victim from the perpetrators and seek refuge in rescue centres and shelters available.

The Kenyan government, civil society organizations, and international partners have implemented initiatives to combat GBV and support survivors. Legal frameworks in Kenya, such as the Sexual Offenses Act (2006) and the Protection against Domestic Violence Act (2015), have been established. The legal framework in Kenya ensures that perpetrators are prosecuted and held to account for their actions as a deterrent measure. Continued advocacy campaigns and public awareness drives are conducted. Their objectives are sensitization of individuals to change the attitudes and behavior patterns that fuel GBV. They address perspectives such as the belief that practices such as domestic violence, child marriages, FGM, and widow inheritance are justifiable and acceptable as forms of expression of love or purity (Kwamboka, 2022). This education is carried out by the government, Civil Society Organizations, and NGOs through GBV campaigns, conferences, and workshops.

Furthermore, economic empowerment initiatives are conducted to curtail GBV. This strategy is key to the empowerment of women and girls by increasing their bargaining power through education and enabling them to participate in income-generating activities (Kwamboka, 2022). Such initiatives include involving women and girls in the implementation of innovation which generates income for them such as through micro-finance entities and community-based organizations like "Turning Pain into Power" and "Soap-making business" in the Kibera informal settlement (UNFPA, May 2022) (UNFPA, June 2022). This tool is effective because it addresses the risk factor of vulnerability which intensifies GBV. Making the victims financially independent equips them with the support they need to sever the abusive ties without the fear of lacking provision for their basic needs.

Kenya also adopted Gender Violence Recovery Centers (GVRC) in the country for the support of GBV victims. These facilities are mandated with the management and prevention of GBV. By 30 June 2023, the GVRC had managed to support more than 58,000 survivors (GVRC, 2023). The centers use varied means to realize their mission. This includes participating in the

drafting of policies addressing GBV such as the National Gender Policy as well as the enactment of Kenyan legislation such as the Sexual Offenses Act 2006 (GVRC, 2023). Furthermore, the facilities conduct several social mobilization initiatives, and convene workshops and conferences on GBV in addition to lobbying and partnering with other organizations such as the UN, Civil Society Organizations, and the Government of Kenya. They also ensure training of different stakeholders in support of addressing GBV through varied means such as the inclusion of GBV as part of the Nursing Diploma Curriculum (GVRC, 2023). These centers also form partnerships with other responders such as the National Police Service to enhance capacity on matters relating to forensic management, referrals, and expert testimonies for court proceedings.

Subsequently, the legal framework, advocacy, specialized response centers, economic empowerment, counselling services, and all other measures aim to assist GBV victims with support and care in addition to reducing GBV prevalence in the country. Despite these efforts, challenges persist in effectively addressing GBV hence hindering progress. The existing challenges include insufficient resources for prevention and response, prevalent coordination issues among stakeholders, barriers that exist culturally and socially, weak mechanisms of reporting, and curtailed awareness.

2.3.2 Technological Response to Gender-Based Violence

There are varied technologies utilized in digital interventions for GBV. Mobile applications are part of the technology used due to the accessibility of mobile devices to a significant percentage of the population. Mobile applications for addressing GBV are, therefore, able to reach an extensive calibre of individuals, even those who do not have consistent access to the internet for those applications that, once installed, do not require access to the internet (Aldkheel & Zhou, 2023). Further, web-based applications have also been developed as part of GBV interventions, and through any device with an internet connection, victims can obtain the assistance they require.

Gender-based violence increases during crises and humanitarian emergencies, such as conflicts or natural disasters (Neetu, Charlotte, Mwangi, Neha, & McGovern, 2021). The advent of COVID-19 pushed the health sector into digitization of access to health interventions such as online therapy. A study conducted by the Portuguese Psychologists Association enquired about the adoption of ICT by psychologists in the provision of their services. The psychologists who responded to the survey indicated that as much as additional precautions would be required for

the use of technology in their practice, it still yielded the desired results and met client needs. Average-experience psychologists were more approving of the utilization of web-based and other technologies in their practices (Dores, Geraldo, Carvalho, & Barbosa, 2020). The COVID-19 pandemic, therefore, brought the world to the recognition of the limitations and gaps of the current systems and hastened the need for alternative means of health interventions to reach more individuals in different circumstances.

Counselling services are crucial for the guidance of a victim of GBV through the path to recovery. Most victims, however, cannot afford the facilities that provide care for themselves so that they can get a chance to live a seemingly normal life. Additionally, with Face-to-face psychotherapy, the providers are insufficient and increase at a slower rate than the demand for mental health facilities globally (Inkster, Sarda, & Subramanian, 2018). Technology is, therefore, of the essence as a delivery for intermediate and supplementary support.

Technology provides a substantially broader network, and access to extensive and unlimited resources, in addition to the layer of defense of perceived anonymity derived from being behind a screen (Aldkheel & Zhou, 2023; Inkster, Sarda, & Subramanian, 2018). Furthermore, the release of ChatGPT caused further acceptance and widespread adoption of technology involving human-machine conversations (Aldkheel & Zhou, 2023). In addition to this, technology provides efficient interventions because online interactions are significantly cheaper and less time-consuming than in-person meetings and can converge much larger groups and individuals, even from across vast distances.

The use of conversational agents to conduct counselling for GBV victims is a researched approach because the technology is easily and widely accessible due to its interoperability (Aldkheel & Zhou, 2023). Furthermore, studies have established that users perceive conversational agents to have the capabilities to handle private and sensitive information more securely without tampering, judgment, or bias hence being inferred to be more dependable conversational partners (Aldkheel & Zhou, 2023).

Aldkheel & Zhou (2023) researched the technological support aspects of conversational agents in caring for survivors of Domestic Violence. Domestic Violence survivors are part of the GBV victims. In their study, they acknowledged that domestic violence poses adverse effects to the survivors in addition to it being prevalent and complicated to manage. The choice of technology was informed by the fact that most survivors refrain from divulging information about their experiences especially in a face-to-face context due to varied factors (Aldkheel & Zhou, 2023).

Privacy, and emotional, cultural, and social reasons are significant hindrances to survivors seeking the assistance they require to process and deal with their encounters. Accordingly, Aldkheel & Zhou (2023) recognized that have the significant potential to facilitate the provision of support and counselling by delivering the survivors a platform that encourages self-disclosure and promotes user engagement through the use of conversational agents.

Studies indicate the different means by which conversational agents are utilized in the Domestic Violence aspect. They highlighted how different AI technologies are utilized to provide support to users. rAInbow is one such chatbot that is embedded in Facebook Messenger. It recognizes the plight of individuals at risk of being abused and the loneliness that comes with the situation in addition to the lack of trusted companions with whom one can share their experiences (AI for Good, 2018). Its role is to train the users and hence enable individuals to pick up on early abuse signs with the distinction of normal and abnormal behavior. Additionally, rAInbow allows people to enquire about their rights as well as offering personalized storytelling whereby the users get to listen to the stories of others who have undergone similar circumstances (World Justice Project, 2021).

A similar technology is the messaging chatbot called 'Sophia' which is integrated into a messaging application or accessible via a webpage for the support of domestic violence victims (Spring ACT, 2022). The chatbot is created with the objectives of assisting individuals in abusive relationships to collect potential evidence by uploading the injustices occurring in their households, assess what their rights are by empowering them with knowledge of contacting the relevant authorities and accessing legal assistance in addition to the victims being educated about their available options (Spring ACT, 2022).

Other technologies developed for addressing Gender-Based Violence include a mobile application with an embedded chatbot modelled to answer queries related to Domestic Violence (Hossain, Najib, & Islam, 2020). The technology would immediately generate information such as contacts to a police station or share instructions on reacting to a given domestic violence event. Similar to other technologies devised for GBV, the intervention is meant to provide a confidential and secure environment where a victim accesses information of the essence concerning their circumstances.

In their study, Aldkheel & Zhou (2023) had the objective of addressing the existing knowledge gaps in the conversational agents' design principles, specifically the chatbots devised for Domestic Violence victims. The participants engaged in the study included 11 professionals

whose work assignments are engaged with survivors of domestic violence (Aldkheel & Zhou, 2023). The tools used for the research were in-depth interviews which delved deep into the Domestic Violence issue, with its impact on the survivors being key. Analysis of the findings of the interview transcripts in addition to literature on the subject were analysed.

The researchers, Adkheel and Zhou (2023), looked into identifying meta-requirements of conversational agents and subsequently classified them into 4 categories. These 4 distinct pillars were trust, language, conversation, and support. Further, the study categorized the identified meta-requirements into several design principles which lay the groundwork for the development and modelling of conversational agents for the support of survivors of domestic violence. Aldkheel & Zhou (2023) researched the use of conversational agents for Domestic Violence survivors and identified the challenges involved, meta-requirements for the technology for the survivors, and derived design principles from the meta-requirements identified. Their findings support this research by guiding the development of desirable features for GBV victims' interactions with conversational agents as an intervention.

2.4 Related Applications

2.4.1 Chomi- Multilingual Chatbot for GBV Victims in South Africa

Chomi is a word used in South Africa to mean "a friend'. Chomi is a chatbot developed by the Shout-It-Now organization based in South Africa as part of response interventions to GBV (Vivier, 2022). It is free and is a WhatsApp-based conversational agent that engages GBV victims in conversation. The chatbot avails information to survivors and provides service referrals to GBV survivors (Shout It Now, 2021). Chomi is multilingual and users can choose to use English or Isizulu, and is currently working on including isiXhosa and Setswana as part of the language options.

The chatbot was developed by including over 640 messages built into the model (Vivier, 2022). It can share cited knowledge and offer anonymous support (Shout It Now, 2021). Its assistance is categorized into 9 support areas which are a connection to support services, safety planning, counselling support, reporting of violence, emergency assistance, information on women's shelters, legal assistance, GBV FAQs, and information in addition to what one should do if they have been sexually assaulted (Vivier, 2022). Chomi, therefore, empowers victims with words of affirmation, assisting them with averting feelings of self-blame and facilitating ways in which they can prevent the occurrence of a repeat incident.

Similar to the developed, Chomi is multilingual as it includes English and isiZulu and is working on Setswana and isiXhosa to further accommodate more South African dialects hence ensuring effective support for the GBV victims in their country (Vivier, 2022; Shout It Now, 2021). Language is key in ensuring inclusivity and effectiveness of the conversation hence this chatbot application includes both English and Kiswahili, the two national languages in Kenya. Further, unlike the developed chatbot application, Chomi is WhatsApp-based which requires the user to have installed this text-messaging platform (Shout It Now, 2021). This developed chatbot is web-based to ensure the user does not need to install the application and users get capability to access the chatbot application through multiple browsers and via a number of platforms such as mobile, desktops and laptops hence making the application easily accessible.

2.4.2 ChatPal: Multilingual Digital Mental Health and Wellbeing Chatbot

Chatpal chatbot effectiveness as a mental health approach was researched by Potts, et al. (2023) for the promotion of the mental wellbeing of individuals residing in rural areas. The conversational agent was created as part of the technological strategies for bridging the gap between the supply of mental health intervention strategies and the exceeding demand for limited resources. Chatpal was developed as a multi-lingual chatbot with the capability to converse in English, Swedish, Scottish Gaelic, and Finnish (Potts, et al., 2023). Additionally, the technology was built to include psychoeducational content, thought diaries as well as breathing and mindfulness exercises, and mood and gratitude logs. The study by Potts, et al. (2023) aimed at establishing the outcomes of exposing individuals to the usage of a mental wellness conversational agent as their primary objective. Subsequently, the study investigated the attributes of people whose exposure to the chatbot resulted in mental health improvement as well as the characteristics of those whose mental wellbeing worsened post-exposure to the chatbot (Potts, et al., 2023). These attributes were part of the secondary objectives of the study.

The methods utilized for the study involved pre and post-intervention with the period of utilizing the Chatpal as an intervention being set at 12 weeks (Potts, et al., 2023). Individuals recruited were from across 5 regions which are Scotland, Sweden, the Republic of Ireland, Northern Ireland, and Finland. The 3 Performance Measurement scales utilized for outcome assessment included The World Health Organization Index, the Satisfaction with Life Scale in addition to the Short Warwick-Edinburgh Mental Well-Being Scale (Potts, et al., 2023). In the study, the evaluation of the impact of the intervention was conducted at pre-intervention as the baseline, midway between intervention as the midpoint, and lastly at the end point of the

intervention. As part of the pre-post intervention, the participants gave written feedback which was collected and processed using

The sample size obtained for the study included 348 recruits of the age range 18-73 years which establishes a mean of 30 years, with 73% of them being female (n=254) and 27% of them male (n=94). The findings from the study determined that there was an improvement in individual well-being not only from baseline to midpoint but also from midpoint to endpoint (Potts, et al., 2023). In contrast, the improvement noted was however did not establish statistically significant scores on the 3 scales aforementioned. The Satisfaction with Life Scale recorded scores of P=.81, the World Health Organization-Five-Well-Being Index recorded P=.52 while the Short Warwick-Edinburgh Mental Well-Being Scale had a performance of P=.42 (Potts, et al., 2023). For the secondary objective measure, the study established that people who had higher interaction with the chatbot were the ones whose recorded well-being scores improved. These individuals were those significantly younger than the people whose well-being scores were reported to have declined post-intervention, recording P=.03 (Potts, et al., 2023).

Furthermore, the examination noted 3 themes derived from user experience categorized as 'negative experiences', 'positive experiences', and 'neutral or mixed experiences.' The individuals who highlighted "negative experiences" or 'neutral/mixed experiences' recorded that as much as they had an overall liking of the chatbot, they faced some barriers in the form of performance and technical errors (Potts, et al., 2023). Concurrently, 'positive experiences' responses were backed by liking the exercises which the chatbot provided. In conclusion, their research proposed that since ChatPal recorded marginal improvements in mental health, even though results were seemingly statistically insignificant, chatbots should be utilized to supplement the varied face-to-face and digital services offered for the improvement of mental well-being. The study further highlighted that their recommendation was to utilize a blended-services approach for addressing mental health. Potts, et al however recommended that the effectiveness of using conversational agents should be further researched.

The developed chatbot has design features similar to ChatPal such as the fact that ChatPal utilizes multilingual capabilities by having the ability to converse in 4 distinct languages which are English, Swedish, Scottish Gaelic, and Finnish. The varied languages are provided to cater to the needs of the population in the rural areas of the 5 regions represented in the study. Similarly, in addition to English, the developed chatbot application includes Kiswahili language to ensure more GBV victims can suitably interact with it. Furthermore, the referrals

and support material in the developed chatbot include the available resources in Kenya. Consequantly, ChatPal chatbot is developed for addressing the general wellbeing of any individual hence is not targeted to the needs of GBV victims. On the other hand, the developed chatbot is specifically developed for use by GBV victims hence the content included is significantly steered towards the improvement of wellbeing of a GBV victim.

2.4.3 Namubot: A Conversational Agent for Sexual Assault Survivors

Namubot is a conversational agent created to act as a counselling tool for sexual assault survivors as an intervention for them due to their struggle with disclosing their encounters in human-to-human conversation. The study by Park & and Lee (2021) researched the burden that sexual assault survivors have when seeking help. Their research included the subjective and psychological burden that comes with a survivor interacting with a new system. Park & Lee (2021) modelled a conversational agent called 'NamuBot' which was devised with the objective that it would provide a burden-free experience for the survivors. In the creation of NamuBot,

They utilized the agile method of system development. Initially, Park & Lee performed a feasibility study that consolidated varied professional stakeholders. For the initial prototype development, Park and Lee used a participatory designing method whereby they incorporated input they received from interviewing professionals involved in sexual assault interventions, which in their case they utilized the police and counsellors. They also carried out co-design sessions for the prototype modelling. They then carried out a qualitative study on the user interaction with NamuBot intending to identify the burden of interacting with the conversational agent and compare this with the human-to-human burden of interaction (Park & Lee, 2021). The study addressed this by allowing the survivors to tell the stories of their past experiences with human interventions and recording their input about their interaction with NamuBot. Furthermore, the victims outlined the kind of support they needed, the weaknesses and strengths they inferred from interacting with the conversational agent, and their recommended solutions to lower the potential burdens of using NamuBot. Subsequently, the study utilized 36 participants comprising 17 professionals (N=17) and 19 survivors (N=19) and used them for the modelling of design features with the potential to lower the CA-bound constraints. These were then incorporated into NamuBot.

The findings from interaction with NamuBot after the CA-bound burden was addressed established that survivors preferred the human-machine interaction over the human-human conversation. The results recorded from the study indicated that 17 of the survivors preferred

to report their encounter to NamuBot in place of professionals such as police and counsellors (Park & Lee, 2021). They recorded that they felt less burdened towards the chatbot compared to the individuals. Furthermore, Park & Lee (2021) examined that the burdens imposed on the survivors by the technology could be alleviated by design features modelled co-jointly by the professionals and survivors.

This research on the development of chatbot borrows from some of the aspects of developing NamuBot. The findings from the study by Park & Lee (2021) identified 9 burdens expressed by survivors towards NamuBot. The burdens were in terms of emotional, financial, time, and availability. Their study looked into the design features which can reduce burdens derived from the CA which were expressed by the survivors. Some of these features are incorporated into the design of the developed. These include multi-stage authentication and a feature for the locking of past conversations to address the privacy and security concerns raised by survivors (Park & Lee, 2021). Furthermore, for the reduction of the emotional burden on the survivors, similar to NamuBot, the developed chatbot includes self-compassion and empowering messages to the victim. This research, therefore, utilized the insights from the creation of NamuBot then tailor-made this for the Kenyan context by ensuring the content incorporated is available in Kenya. Furthermore, for the developed chatbot to be more suitable to Kenyan victims, it includes both English and Kiswahili languages hence ensuring that the chatbot has inclusivity. This study however does not use co-design principles or collect its own data set as done in creating Namubot, but utilizes the findings from this and other studies to come up with a the GBV counselling chatbot.

VT OMNES VNVM SINT

2.5 Conceptual Framework

The framework of this technology is the development of a counselling chatbot for GBV victims to hold conversations regarding their circumstances for the improvement of the individual's well-being. While the user interacts with the chatbot's counselling module through the Web application interface provided, the system simultaneously gathers the input, carries out an analysis and processing of this input, stores it in a database then the subsequent generation of a response (Trappey, Lin, Hsu, Trappey, & Tu, 2022). The processing involves the identification of intent, management of the dialog, and interaction with the domain file data to enable the model to devise a suitable response. Sentiment analysis is incorporated in this process because the chatbot is a counselling conversational agent hence it examines the sentiment governing the text input by the user and ensures the output processed by the model

also has an appropriate attitude aligned to and addressing the felt needs of the user (Rathnayaka, et al., 2022). The input and generated output are in English and Kiswahili based on the language of the user input.

The review of 3 related applications and the study by Aldkheel & Zhou (2023)reviewing the effectiveness of conversational agents for the support of Domestic Violence victims informs this study's best practices of modelling a suitable chatbot for counselling GBV victims in Kenya. The recommended design principles and meta-requirements highlighted the importance of ensuring the implementation of a suitable engagement between the chatbot and the user (Aldkheel & Zhou, 2023). The anatomy of such an engagement involves creating an environment that is positive and comfortable such that the individual feels heard and safe (Chowdhury & Neuhaus, 2019). Accordingly, this framework ensures a conversational flow similar to, but not a substitute for, professional healthcare facilities (Rathnayaka, et al., 2022). The conversation flow fundamentally includes a greeting to initiate the conversation, a discussion steered by the user, and a closing of the engagement. Consequently, the conversation includes messages of positive reinforcement to ensure that the user feels encouraged (Rathnayaka, et al., 2022). Accordingly, the conversation is personalized to the support needed by the user since they steer the conversation. Therefore, the framework of this conversational agent includes 4 major components for the improvement of the victim's emotional well-being including the anatomy of engagement to ensure the user is appropriately engaged in the conversation, sentiment analysis, and emotion detection component to determine the attitude and well-being of the user at that instance, maintenance of a personalized experience as the third component and incorporation of positive reinforcement (Rathnayaka, et al., 2022). This framework is illustrated in Figure 2.1 below.

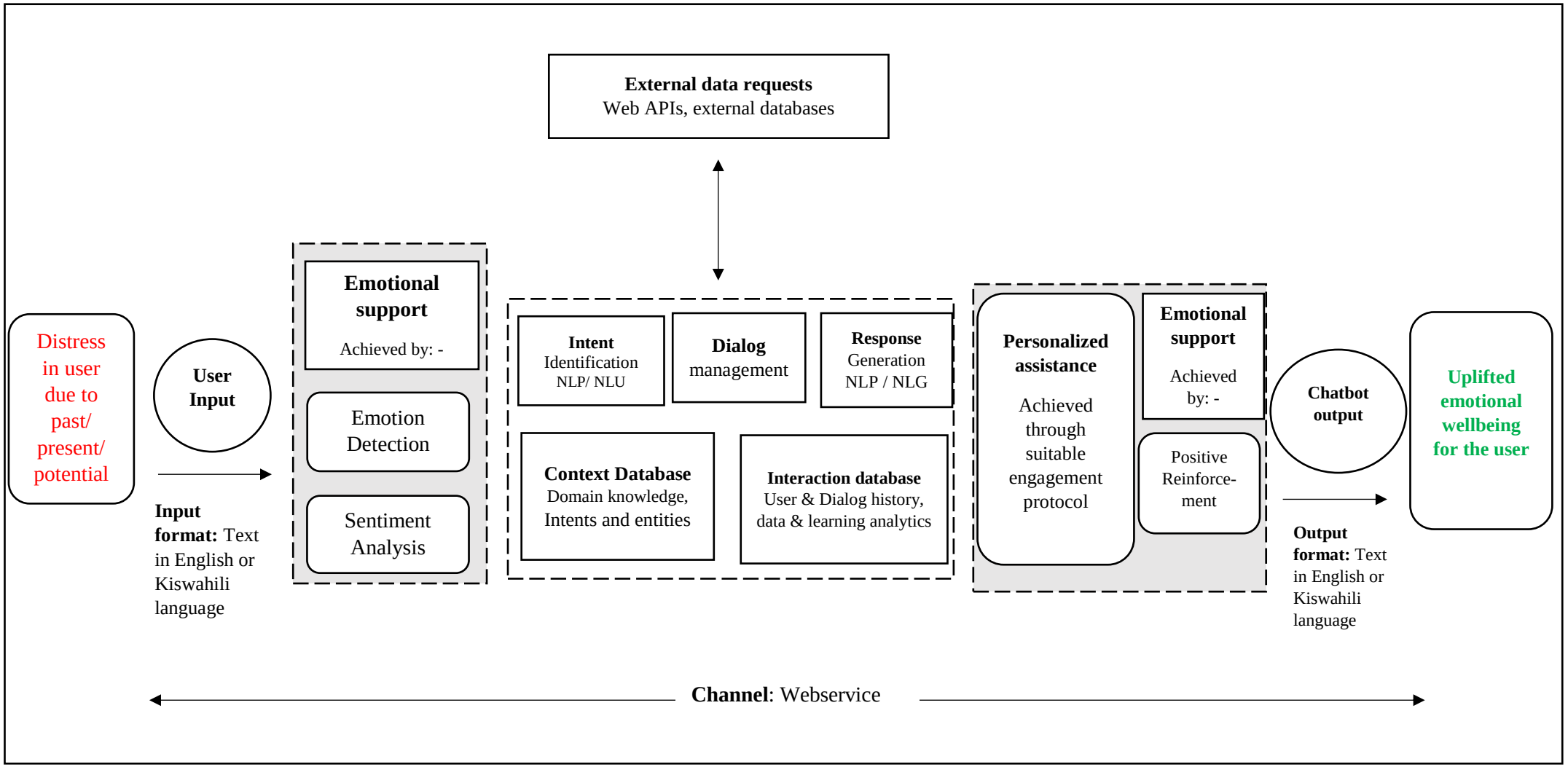


Figure 2.1: Conceptual Framework of the Study

Chapter 3: Methodology

3.1 Overview

This methodology chapter is guided by the specific objectives in Chapter 1 of this study, the problem being studied in addition to the research design used in related studies as reviewed in the previous chapter, all geared towards the attainment of the main objective. The activities covered in this chapter are the research method utilized, the development methodology, the nature of the data set for training and testing the model, the methods and setup of model, and the integration of the findings into the development of the final product.

3.2 Experimental Research Design

This dissertation puts forward an experimental research study aimed at resolving a real-world challenge facing the globe and the adverse effects of Gender Based Violence in Kenya on the victims in addition to contributing to the UN-SDG 5 (Neetu, Charlotte, Mwangi, Neha, & McGovern, 2021). This study develops a chatbot application for use by GBV victims in Kenya for counselling and examines its effectiveness using NLU confidence score for appropriate intent identification and subsequently utilizes Fuzzy Matching Token Set Ratio to select the best matching response out of the listed responses for the identified intent. The developed chatbot receives user input in English or Kiswahili language, processes it to identify the intent and accordingly, generates an appropriate response in the same language. The target group of the chatbot development is the Kenyan context hence the chatbot application includes referral services available in Kenya in addition to recommended GBV grounding exercises. This conversational agent is embedded on a web application for access by potential users using a URL on a browser.

3.3 The Chatbot Application Development

The development of the Chatbot application was to be executed using the following outlined steps:

i. Analyzing the challenges experienced by GBV victims.
ii. Analyzing the weaknesses of the existing interventions to GBV.
iii. Developing a machine learning model for GBV counselling in English and Kiswahili.
iv. Validating the developed model.

v. Integrating the developed model into a web application.

3.3.2 Developing a machine learning model for GBV counselling in English and Kiswahili

3.3.2.1 Setting up the Machine Learning Model

An existing open-source machine learning framework called Rasa was utilized for the development of the chatbot application. This framework contains two major modules merged which are the Rasa Natural Language Understanding (NLU) section for the comprehension of the user messages and the Rasa Core module for dialogue management. The choice of Rasa as the framework to create the chatbot application is because it is the most suitable framework when customization of the model to a given context is crucial. Python programming language was utilized for coding commands for the Rasa environment during the development of the chatbot application. The process required the installation of the relevant Rasa modules for comprehension of user input and components required for dialog management.

The chatbot application was developed as a new Rasa project within the Rasa environment. The next step was the model configuration file where the Core and NLU components of the chatbot were defined in terms of the pipeline to be utilized, language and policies to be implemented. Subsequently, the dialogue management component executed by Rasa Core was designed to indicate how the chatbot application would respond to user input. This was done by writing stories to teach the model how to respond by identifying the entities and intents then responding and actioning accordingly. As part of objective 3, the domain of the model was defined which specified in the domain file the inputs that the model should expect, the subsequent actions to take, the expected responses, and what the model is required to store.

3.3.2.2 The Dataset

Consequently, the attainment of the third and fourth objectives involved training and validation of the model using a specified data set. Secondary data in the GBV subject in English and Kiswahili was utilized to train the model. The choice of secondary data for training the model was due to the time constraints of collecting sufficient primary data (Despard, 2020). This is because a sample size for acquiring primary data would be inadequate for inferential statistics and to be a valid representative of the target population. Additionally, secondary data is readily available in significant volumes from varied agencies and government organizations (Despard, 2020). Furthermore, previously collected data is desirable because of the large sample sizes which provide a more accurate reflection of the population. Additionally, the size of the

training data is of the essence due to studies that indicate that a large dataset is vital to suitable performance by an AI system (Brynjolfsson & McAfee, 2017).

The dataset used for training and validating of the chatbot application model was obtained from an expert community website called Counselchat.com whose platform is a linkage between users and verified therapists (Bertagnolli, 2020). In this platform, verified counsellors provided responses to questions asked by users hence making it a platform for helping therapists to build and enhance their reputation while at the same time making meaningful contact with users who are potential clients. This data set is, therefore, high quality because the individuals who are the source of the responses are qualified counsellors. The dataset was availed publicly when Bertagnolli (2020) contacted the founders of Counselchat website and was given all of the website's data for use. This was then combined with the data which Bertagnolli (2020) scraped from the website where licensed therapists counsel users on real life issues. The goal of availing this dataset was to provide an open source dataset of high quality from quality counselling responses. This counselling dataset which is in .csv format has 2,128 entries and 10 columns (Bertagnolli, 2020). This dataset acted as the foundation for teaching the chatbot model the basics of emotional support provision and guidance.

ID	Column	Function
1.	'questionID'	provides a unique identifier for every question
2.	'questionTitle'	title that the question had on counsel chat platform
3.	'questionText'	houses the body of the question which an individual posed to the counsellors
4.	'questionLink'	is a representation of that question's last location
5.	'topic'	title of the question asked by the user
6.	'therapistInfo'	includes the name and specialty of the therapist responding to the question
7.	'therapistURL'	a link to the bio of the therapist on the Counselchat platform
8.	'answerText'	the counsellor's response to the question
9.	'upvotes'	is a total of the upvotes received for the specific answer on the platform
10.	'split'	The data had already been divided into sections for training, testing and validating the Machine Learning model

Table 3.1: The Dataset Columns

Further, with the chatbot application having capabilities of conversing in both English and Kiswahili languages, this English-language counselling dataset was translated into Kiswahili with the intent labels and original context maintained. The chatbot was developed in such a way that it has capability to recognize the entities and intents in both languages. Therefore, for each intent and entity, the NLU Rasa file has examples in both English and Kiswahili languages. For the achievement of a bi-lingual capability chatbot, the English and the Kiswahili language datasets were combined into a single dataset such that for each training example, there is a label included on the corresponding language, either English or Kiswahili. Accordingly, for each intent, responses in both English and Kiswahili were be created such that the developed chatbot can respond appropriately in terms of language to the user input. Therefore, this allows the users to utilize the language they prefer hence the chatbot adopts to the user's preference for the duration of the conversation (Vainu, 2021).

Subsequently, this dataset was converted from a CSV file to a Rasa framework-acceptable format. This is the YAML format which is a data serialization human-readable language. The training data was split into multiple YAML files with varied combinations of stories, NLU data, and rules in addition to the specification of the version key. The model was also subjected to the validation dataset to evaluate and monitor the model's performance in addition to checking for overfitting and fine-tuning of the hyperparameters defined during the configuration stage for guiding the Machine Learning model through the learning process (Myrianthous, 2021). To check that the model responds as expected and makes appropriate predictions after the training phase is complete, the developed model was subjected to GBV related queries using the Rasa Shell and Interactive module to check the appropriateness of responses (Myrianthous, 2021).

3.3.6 Integrating the Developed Model into a Web Application

Once the chatbot model was trained and validated, it was then deployed on a web page where users have access to it for interaction with the chatbot application. On the Rasa platform, a command line was used to check that the chatbot model was set for export and another command line used for export. The chatbot application user interface was a developed web application with other content including referrals within Kenya and recommended grounding exercises for GBV victims. The web application was hosted on the local machine used for development and includes a chat interface which allows the user to interact with the trained chatbot model through an endpoint after providing a message as input then viewing the generated response from the chatbot model which is sent from the Rasa model to the web

application through the endpoint. The web application used as the user interface was created using JavaScript, HTML and CSS with HTML and CSS for frontend development and JavaScript to provide backend logic of sending and receiving messages from the chatbot model through HTTP POST requests to the Rasa server and receiving responses (Rasa Technologies , 2023). The chatbot is accessed by users through navigation to the URL of the web application.

3.4 Application of Iterative Methods in the Chatbot Development

This study is aimed at the resolution of the global issue of GBV causing inequalities in society. It develops a conversational agent that accepts GBV text query in English and Kiswahili languages, processes this input from the user, picks out the intents and entities then compose a response based on the GBV knowledge database available with pre-programmed scripts. The adopted process for the study was an initial review of previous studies conducted outlining the meta-requirements and design principles to guide the building of a conversational agent for counselling GBV victims. The Rasa framework was utilized for the setting up the required configuration rules for the developed conversational agent in addition to training, validation and, testing of the Rasa Chatbot model using an English and Kiswahili pre-processed dataset which ensured that the chatbot has bi-lingual capabilities. Subsequently, once the developed model was validated, it was embedded in a web page whereby users are able to access the chatbot using a URL which redirects them to the web page where the chatbot is embedded. This web page also include referrals and other material for the GBV victim to get information to guide and support them through their journey to recovery.

For achievement of this development, Iterative development principles were utilized. They were executed by having direct collaboration and communication with this dissertation's supervisor through establishment of a direct channel of communication and feedback via emails. Development also emphasized the delivery of a working product, in this case the development of a functional chatbot, based on regular communication and feedback from this dissertation's supervisor, throughout the process, who is a representative of the interests of potential users. This chatbot application development also adopted the principles of responding and adjusting to change, as opposed to following a plan, based on feedback by incorporating the improvements and changes suggested by this dissertation's supervisor.

This development was divided into time-bound and short iterations referred to as 'sprints' whereby each sprint focused on specific features and functionalities of the chatbot hence each sprint delivered value in terms of a functional aspect of the chatbot. The end of each sprint

involved a review of the progress and chatbot functionality with the dissertation supervisor for discussion and collection of feedback, making of improvements on the development process and a subsequent adjustment of the direction of the development based on the findings of this review meeting (Agrawal, 2019). Therefore, in subsequent iterations the areas identified for enhancement during the post-sprint review meeting were prioritized and carried out hence ensuring incremental improvements, flexibility and adaptability (Agrawal, 2019). Regular updates, communication and openness to feedback were of the essence during this application development to foster collaboration and transparency. A product backlog was used as a listing of the development tasks, features and improvements for purposes of prioritization of features and tasks. A breakdown of the time-boxed and short iterations in form of sprints that were utilized for this chatbot application development is in Appendix 1.

3.5 Validity and Reliability of the Study

The validity of this dissertation was ensured by conducting a review of literature on the impact of GBV on victims and a critique of the existing interventions in addition to studies regarding the best practices and principles to incorporate for the effectiveness of a conversational agent developed for the support of GBV victim (Carroll & Goodfriend, 2022). Furthermore, the sources used to develop the content which were incorporated on the chatbot platform interface are scholarly articles and documentation in addition to books discussing the relevant guidelines by humanitarian organisations such as the UN for providing remote psychosocial support to GBV survivors. Augmentation of the counselling dataset was carried out to include specific GBV intents and responses from the guidelines on psychosocial support by UNFPA (2020) to ensure that the specific needs of the GBV victims are catered to. The chatbot model was subjected to data obtained from conversation between users and verified therapists hence ensuring that the chatbot application has the capability to comprehend a counselling environment and subsequently provide appropriate and valid responses to users. Furthermore, during the process of development, the developed model was subjected to GBV related queries to ensure that processes the input by a suitable generalization then generating appropriate and valid responses (Carroll & Goodfriend, 2022). On data reliability, open-source secondary dataset was utilized for training and validation of the chatbot model which was obtained from a credible source because the dataset includes questions asked by users who needed counselling and responses given by professional and Licensed therapists on a website called Counselchat.com.

The consistency and accuracy of the obtained dataset is demonstrated by using data from the same source which is Counselchat.com which includes counselling set-up responses by licensed therapists which infers that the counsellors' responses are guided by their professional mandates and protocol. The interrater reliability was demonstrated by the involvement of different evaluators throughout the process of the development (Middleton, 2023). These included the periodic presentations during class for review of the development process by the dissertation class and the dissertation coordinator in addition to periodic meetings with the dissertation supervisor for review hence ensuring that different parties were involved in providing feedback about the chatbot application (Middleton, 2023). Additionally, due to the iterative nature of this study, regular review and feedback cycles between sprints were conducted which included a review of the performance reliability of the chatbot. The feedback from the dissertation class and the dissertation supervisor were incorporated into the development of the Chatbot for continuous improvement of the chatbot's reliability. Additionally, this dissertation was subjected to an ethical approval process which enhances the validity of the research (Bhandari, 2023).

Furthermore, the chatbot application was validated using NLU confidence score and fuzzy matching metrics in addition to conducting Rasa Interactive sessions. The NLU confidence value was used as a scoring of certainty that the correct intent was identified for the input by the user. Additionally, the Fuzzy Matching Token Set Ratio Score was utilized to check the matching of the question string to the listed responses in the identified intent and selecting the response with the highest Token Set Ratio score and generating that as the response by the model. The Fuzzy Matching was used by comparing the content of the question to the content of the responses while the NLU Confidence score was used to review the understanding of the NLU engine and selection of the appropriate intent. Furthermore, the Rasa Interactive session was used to query the chatbot model by providing an input then reviewing the displayed response on whether it is relevant and suitable to the question asked. Consequently, on querying the chatbot model using rasa interactive session, it is set up to display the NLU confidence level and Fuzzy Matching Token Set Ratio score.

3.6 Ethical Considerations

Ethical considerations in this study informed the sources of data and methods used to obtain the data considering the acceptable and unacceptable stipulations by Ethical standards. The resources used for the development of this study including previous works were obtained from

credible sources and the references cited. Furthermore, a similarity report is affixed to Appendix 2 of this dissertation to indicate the plagiarism index hence demonstrating that research misconduct has not occurred for a similarity score below the threshold (Bhandari, 2023).

Additionally, the dataset utilized is obtained from the public domain and via acceptable means because it is a dataset availed by the founders of a website called Counselchat.com where verified therapists interact with real life problems of actual users and the counsellors provide feedback to the users in response to their query (Bertagnolli, 2020). The source of this data indicates that their aim of disseminating this dataset is to ensure that high quality counselling data is available for training Machine Learning models. Additionally, translation of this dataset was carried out to convert the data from English to Kiswahili language by an individual with a high Kiswahili and English languages' proficiency hence ensuring that the intended meaning of the data was maintained in addition to context preservation and data consistency. For quality assurance of this process and ethical considerations of determining that the translations and responses are ethically sound and culturally sensitive, the dissertation supervisor reviewed the translated dataset to check for the accuracy and fluency in addition to ensuring that potential errors were caught and improvements of the translation were incorporated.

In addition, this dissertation underwent several examination stages which included a review of the ethical component of the research. These are the presentations in the dissertation class where colleagues and the dissertation supervisor critique the study's ethical standards, a dissertation proposal examination by evaluators within the University as well as the final dissertation examination by both internal and external examiners of the University. Consequently, this dissertation was submitted for ethics approval where it was subjected to a review by an Institutional Review Board which consists of a committee of experts to ensure that the objectives of the study and the research design follow the code of conduct of the institution and that it is ethically acceptable (Bhandari, 2023). Therefore, development of the chatbot application did not commence before ethical approval was granted and a research License obtained from the National Commission for Science, Technology & Innovation.

Chapter 4: System Design & Architecture

4.1 Introduction

This chapter is a description of the design of the chatbot application in two aspects. First, this chapter looks into the requirements analysis of the chatbot application development and describes all the functional and non-functional requirements (Tiun, Mokhtar, Bakar, & Saad, 2020). Second, it illustrates the planned application architecture by use of Unified Modelling Language tools including an overview of the application architecture, Use Case diagram to demonstrate the different interactions of a user with the application in addition to a Sequence Diagram for the detailing of operations conducted and the order their interaction and a Graphical User Interface Wireframe (Letaw, 2024).

4.2 Requirements Analysis

In this section of the study, the requirements for the development of the chatbot application are described as divided into two areas which are the functional and non-functional segments (Tiun, Mokhtar, Bakar, & Saad, 2020).

4.2.1 Functional Requirements:

i. User Interaction: The chatbot should be able to accept a text input from a user and provide a response.
ii. Multilingual Support: The chatbot should be able to interact in both English and Kiswahili based on the language of the user input.
iii. Conversation flow: The chatbot should support for basic conversation functionalities such as greetings, asking questions and providing information.
iv. Intent Recognition: The chatbot should have the ability to recognize intents from user messages using NLU capabilities.
v. Map intents to appropriate responses: The chatbot should understand user intents and pick an appropriate response to the query.
vi. Maintain context within a conversation: The chatbot should be able to have a coherent interaction and handle multi-turn conversations for complex interactions.
vii. Deployment: The chatbot should be deployed on a web application for accessibility to users.
viii. Endpoint for Receiving User Input and Sending Bot Responses: The chatbot should provide an endpoint that accepts HTTP POST requests to receive user messages or

input from the web application and sends to the chatbot for processing and an endpoint that sends the response from the chatbot back to the web application for display to the user.

ix. Error Handling: The chatbot should handle errors gracefully, providing clear and helpful messages to users.

4.2.2 Non-Functional Requirements:

i. Performance: The chatbot application should have minimal response time to ensure a seamless user experience.

ii. Scalability: The chatbot application should be able to handle multiple concurrent users and scale with increasing user demand.

iii. Reliability: The chatbot should be available and responsive under normal operating conditions, not crash during use and alert in case of failures.

iv. Usability: The chatbot application interface should be user-friendly and provide clear instructions and guidance for users interacting with the chatbot.

v. Compatibility: The chatbot should be compatible with a wide range of web browsers and devices.

vi. Maintainability: The chatbot application should be simple to support and maintain.

4.3 Chatbot Application Design

The architecture of the chatbot application is described using Unified Modelling Language in the form of an overview of the application architecture, Use Case Diagram, Sequence Diagram and the Graphical User Interface Wireframe.

4.3.1 Chatbot Application Architecture

The overall application architecture involves pre-processing of the secondary dataset which is in .csv format and English language. This pre-processing includes translation of the dataset into Kiswahili using Google Translate as the Computer Aided Tool and quality checks post-translation to come up with a multilingual dataset. The other section of pre-processing is removal of special characters, detection of null values, conversion to lower case and dropping of unnecessary columns. The succeeding step is the conversion of the resulting dataset into YAML format files appropriate for the Rasa Natural Language Understanding file, the Rasa Domain fail which contains responses and actions in addition to the Rasa Stories and Rules files. In this format, the data is then used for training and testing of the chatbot model set up as a Rasa Project. Consequently, the trained model is embedded on a web application which is

hosted locally. The user interacts with the chatbot model via the web application by providing a text input which is posted to the chatbot model through an endpoint. The query by the user is processed by the trained chatbot model by identification of an intent through NLU and generation of a suitable response based on the Rasa domain file responses and custom actions. Accordingly, a response is generated by the model and passed via an endpoint for display on the web application. This chatbot application architecture is illustrated in Figure 4.1 below.

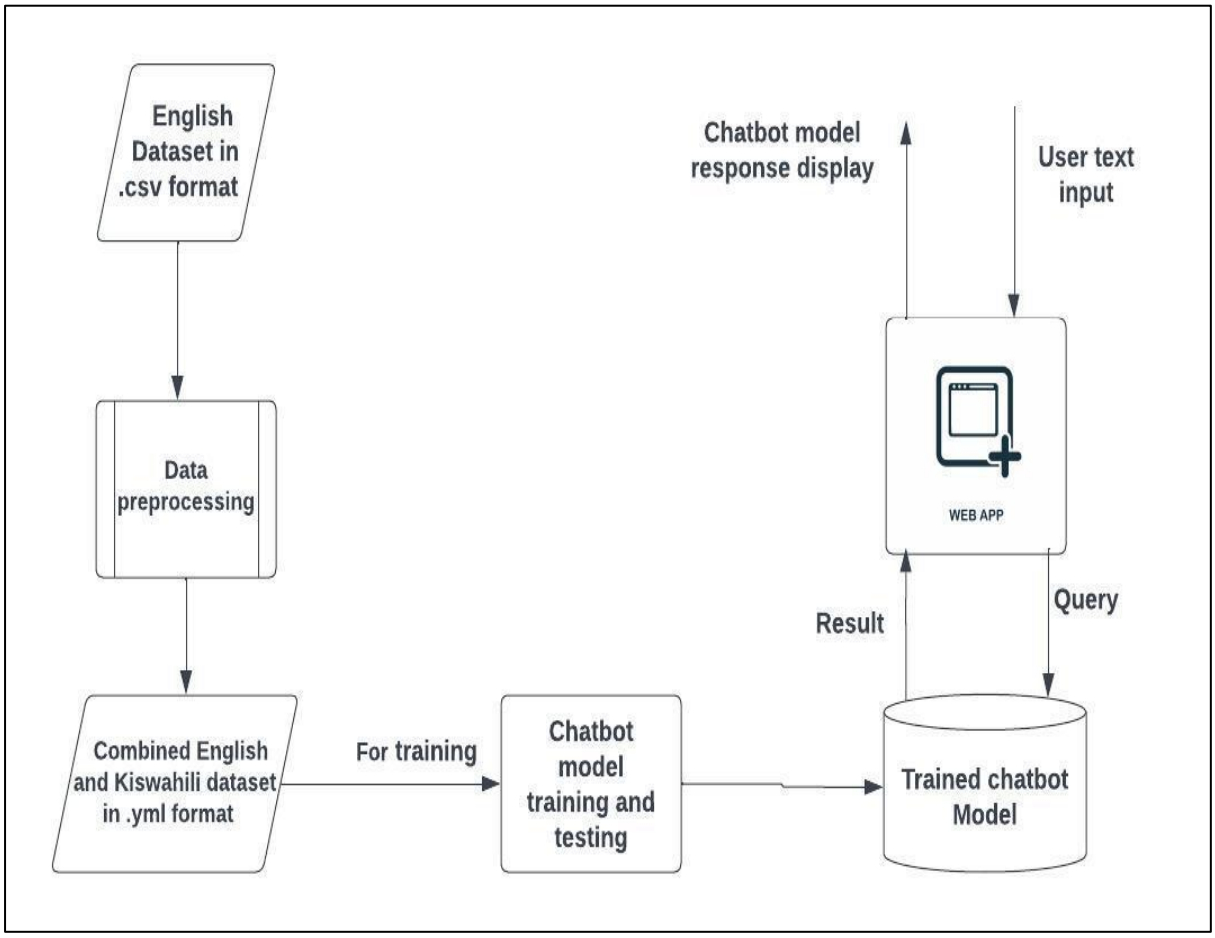


Figure 4.1 Chatbot Application Architecture

4.3.2 Use Case Diagram

The Use Case Diagram is key in providing illustrative representation of different actors interacting with the application. The actors in this Chatbot application include the administrator and general users who access the application to interact with the chatbot. The administrator sets us a new Rasa project for developing the chatbot, then trains and tests the chatbot model using pre-processed data in YAML format as described in chapter three and five. The administrator also creates a web application to act as a user interface through which users

interact with the trained chatbot model. The general user is the second actor and is characterized by an individual accessing the web page by following the provided url. The user lands on the home page and can either stay on the home page or navigate to the linked pages using the links provided. In addition, the user can input text in the chatbot interface provided on the home page of the web application then view the response generated by the chatbot. The chatbot interface on the web application is connected to the chatbot model through endpoints hence inputs from users are passed onto the chatbot model then responses from the model passed back to the user and displayed on this intetface. The web page also contains information on referrals to Kenyan based organizations of the essence to a GBV victim in addition to information on grounding exercises recommended by GBV response organizations to help victims with mental, physical and soothing grounding which helps individuals managing overwhelming feelings and anxiety. This Use Case Diagram is illustrated in Figure 4.2 below.

VT OMNES VNVM SINT

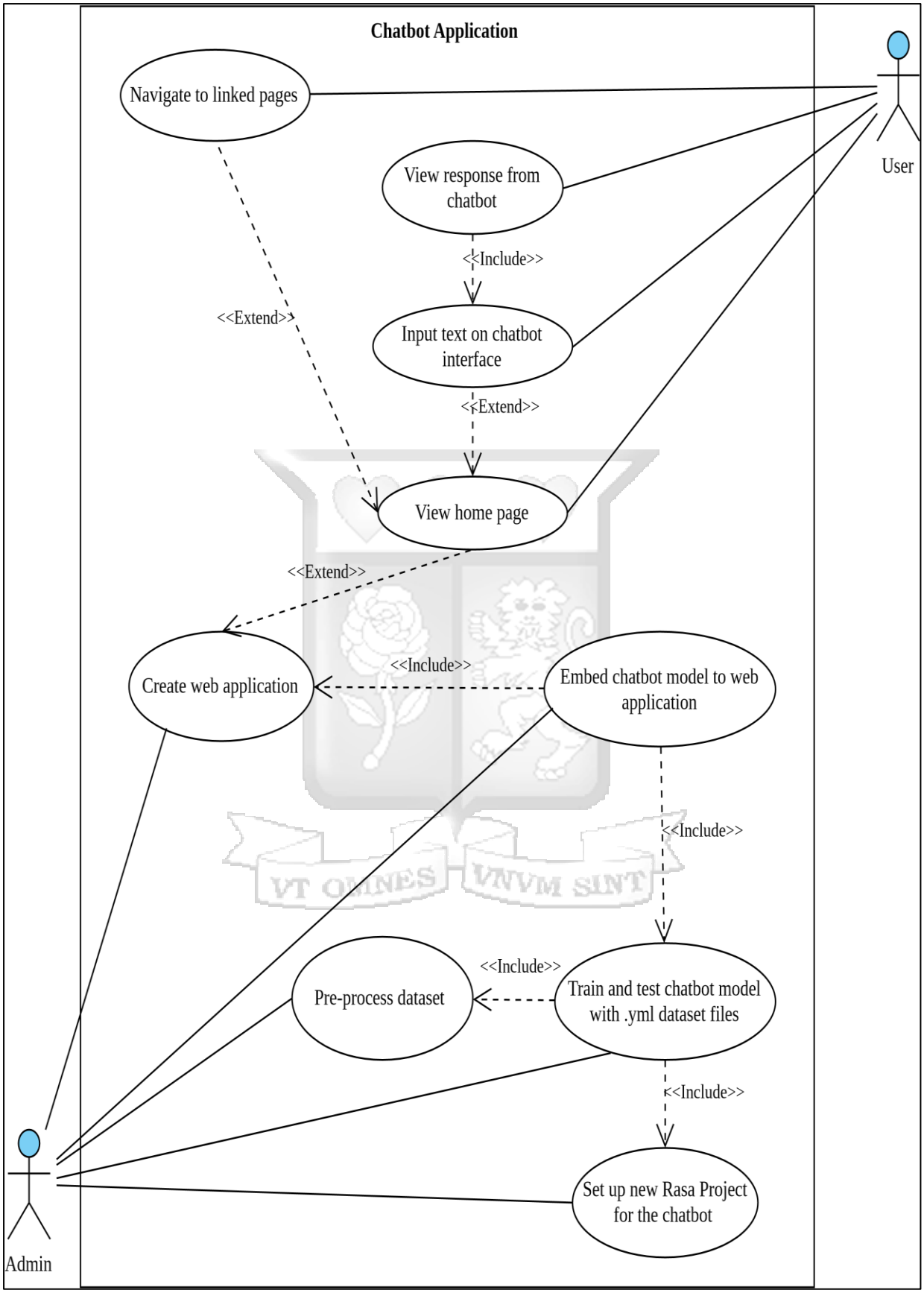


Figure 4.2: Chatbot Application Use Case Diagram

4.3.3 Sequence Diagram

The chatbot application's sequence diagram is an interaction diagram which illustrates the operations conducted between the objects involved. It shows the order in which operations occur in terms of time by the use of the vertical axis from the top being earliest to the bottom being latest in addition to the objects interacting and their lifelines (Alvin, Peterson, & Mukhopaghyay, 2021). The actor in the chatbot application is the user while the lifelines involved are the web application and the Rasa chatbot model. The messages sent within the chatbot application begin with a user, who is the actor, accessing the chatbot application by the use of a url on the browser. On accessing the web page, the user can view the home page then through the home page, navigate to the linked pages which are the referrals page and the grounding exercises page. On the home page, the chatbot interface is also included. The user then types a message on the text editor provided on the chatbot interaction interface. On entering this message, the web application forwards this message to the Rasa chatbot model for processing through an endpoint. When the chatbot model receives the input, it identifies the intent using the NLU component and using this, generates an appropriate response using the stories, rules and domain components of the model. The next interaction is the Rasa chatbot model sending the generated response back to the web application through an endpoint. The web application then displays this response for the user to see, being the last interaction. This cycle repeats itself as long as the user provides an input on the chatbot interface because it is what prompts the chatbot to respond since the conversations are driven by the user.

VT OMNES VNVM SINT

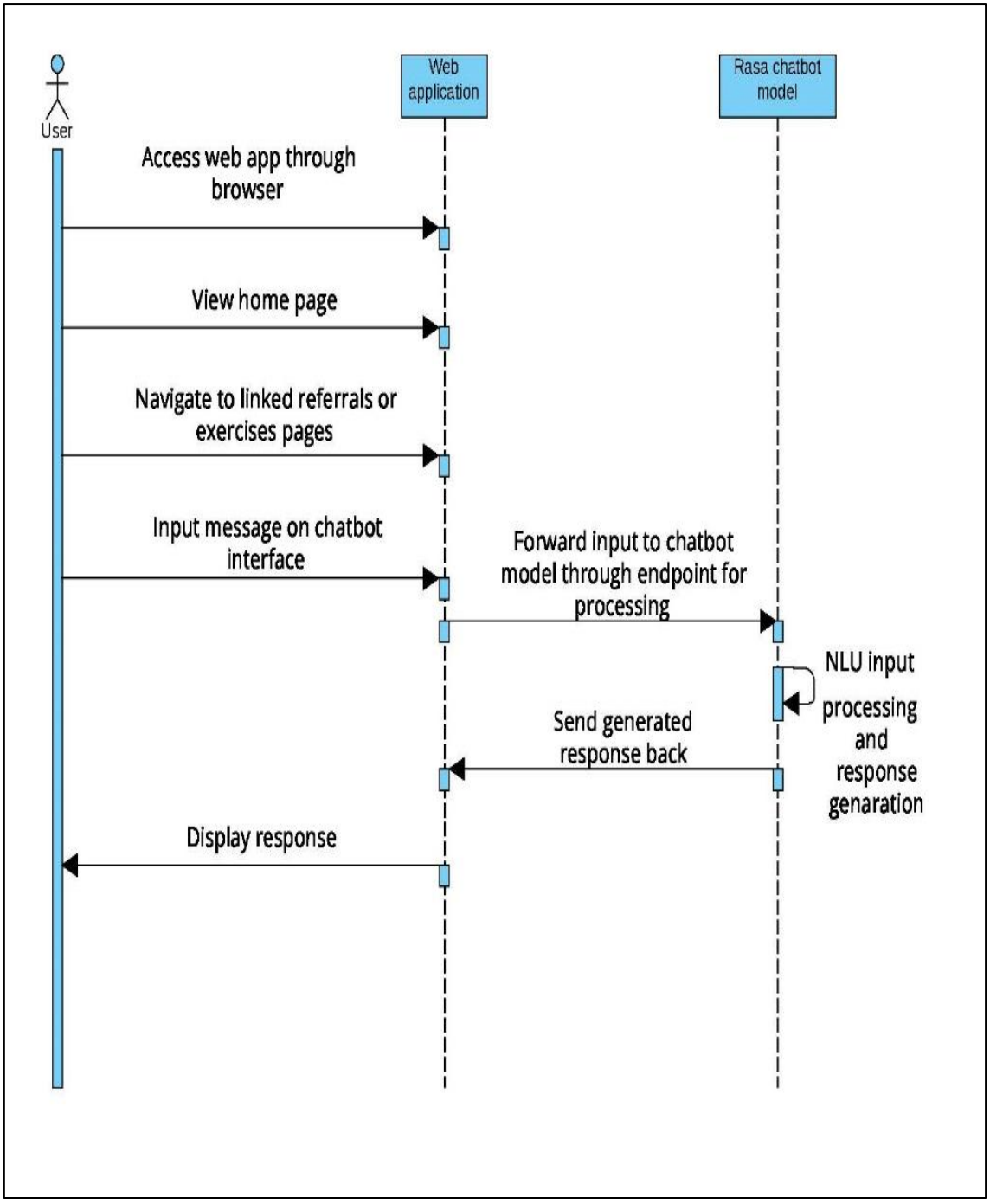


Figure 4.3: Chatbot Application Sequence Diagram

4.3.4 Chatbot Application Wireframe

The wireframe of the chatbot application is the visual representation of the chatbot's user interface showing a basic sketch of what the user views when they follow the url to the web page where the chatbot is embedded. The user interacts with the chatbot by typing a message in the text editor section and view the response from the chatbot through the provided chat box. In addition, the user gets access to referral organizations by clicking on the linked page where hotline numbers provided by different organizations within Kenya which can offer intervention in the event of an emergency and access to further information regarding GBV. Consequently, the web application also provides recommended grounding exercises which would assist a victim in de-escalating anxiety and distress as guided by The Mental Health and Psychological Support Minimum Service Package (Brake, Willems, Steen, & Ducker, 2022; Duckers, Hoof, Willems , & Brake, 2022). It includes guidelines that act as a toolkit for domestic violence survivors to provide ways of soothing, mental and physical grounding (Mental Health and Psychosocial Support Minimum Service Package, 2023). The wireframe diagram is as illustrate in Figure 4.4 below.

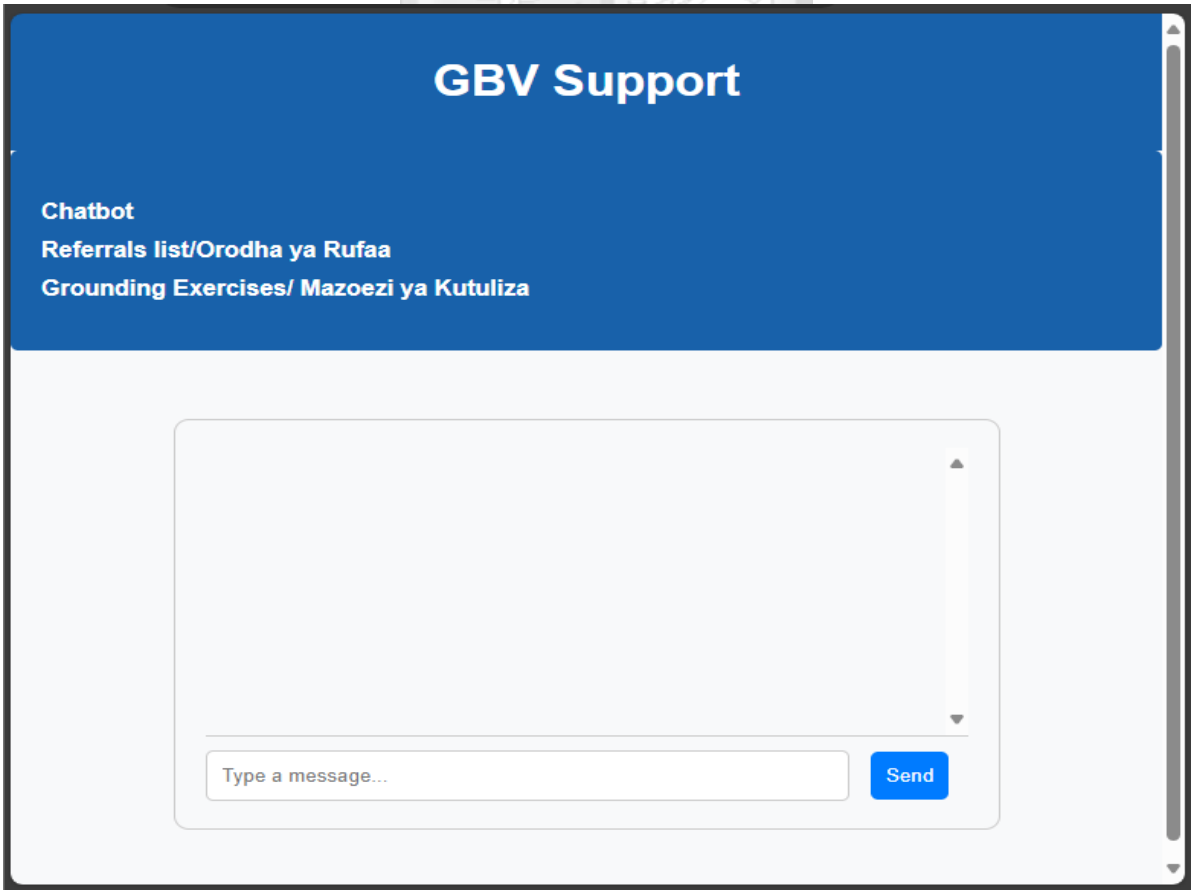


Figure 4.4 Chatbot Application Home Page with Chatbot Interaction Section

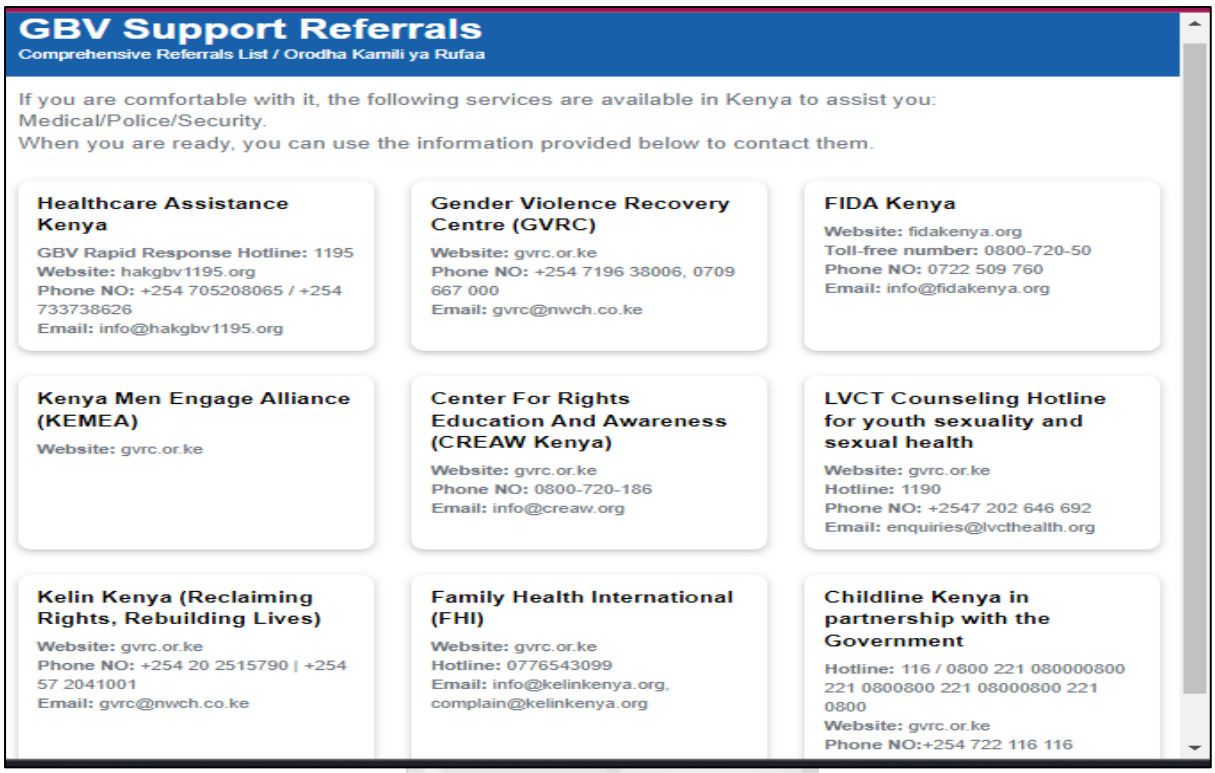


Figure 4.5: Chatbot Application Referral Services Page

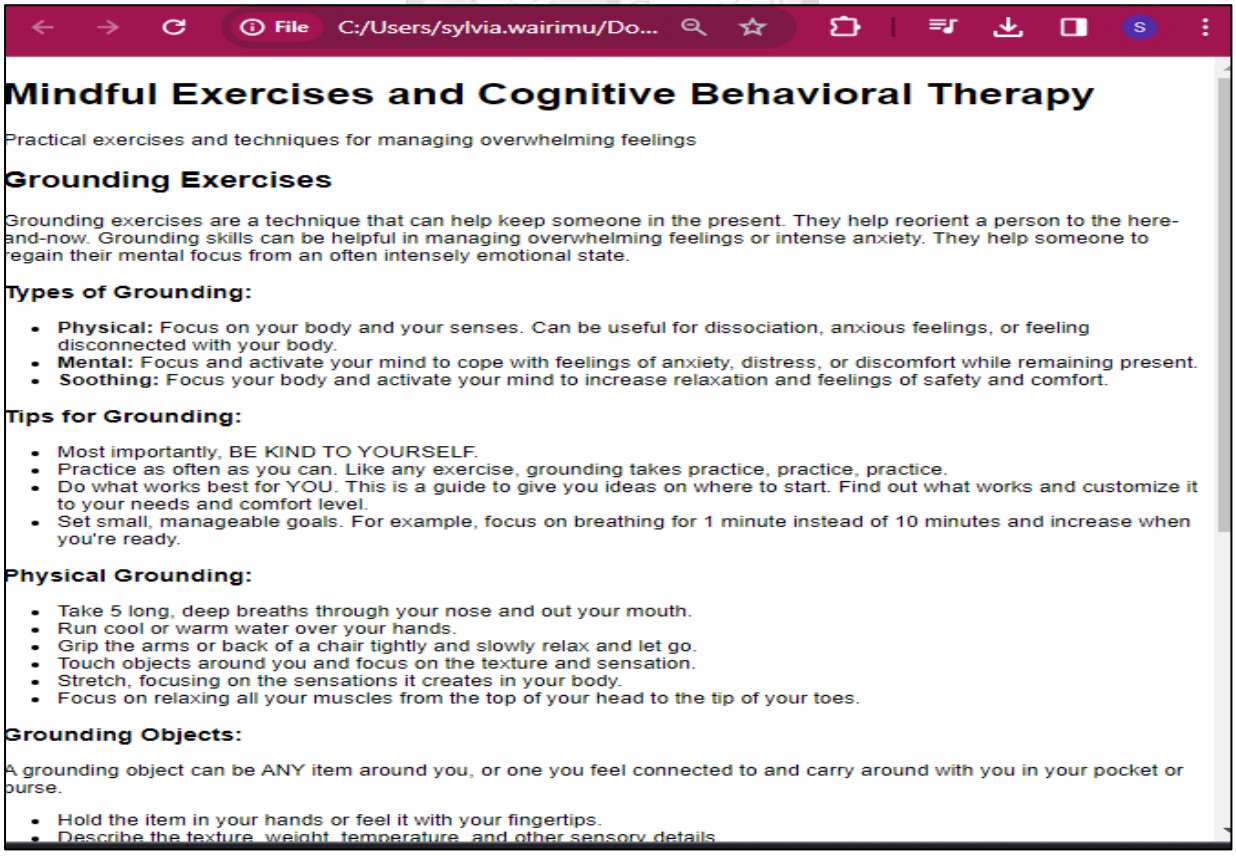


Figure 4.6: Chatbot Application Grounding Exercises Page

Chapter 5: Chatbot Application Implementation and Testing

5.1 Introduction

This section of the study looks into the implementation process of the chatbot application including a detailed description of the components used in the development and the development environment utilized in the implementation process. Furthermore, the data pre-processing and multilingual integration to have both English and Kiswahili incorporated in the dataset. Furthermore, this chapter describes the process of setting up of the Rasa project in the development environment, the setting up of the files and updating of the NLU, Stories, Rules and Domain files to include the training data files extracted from the counselling dataset. Testing of the chatbot is also discussed covering the interaction with the model using the Rasa Interactive session module where GBV related queries were made and responses reviewed to examine their appropriateness. Consequently, this section of the study looks into the deployment of the chatbot application on a Web application as the user interface in addition to other content such as referral services in Kenya and grounding exercises included for provision of information to the chatbot application user.

5.2 The Chatbot Application Components

The chatbot application was developed using Rasa AI framework which is an open source AI framework that is utilized for the development of conversational agents by training and tuning of a model using a suitable dataset to achieve the desired context. The trained chatbot model was trained using pre-processed data to enhance intent recognition and response generation based on the counselling dataset provided. The trained chatbot model developed using Rasa was then deployed on a web application which provides an interface for users to interact with the chatbot model. The web application interacts with the chatbot model through end points. The web application was hosted locally.

5.2.1 Rasa AI framework

The chatbot application is developed by creation of a new Rasa Project and modification of the project's files using training data to come up with updated model which can identify the subject intents and generate appropriate responses (Rasa Documentation, 2024). Rasa utilizes YAML format for its files to enable training of the model. The files used for this training are the Stories, Rules, NLU and Domain files whereby the domain includes the responses and custom actions.

The NLU files contains utterances by users which are grouped in terms of intents in addition to each intent containing training examples listed under the key word “examples” (Rasa Documentation, 2024). Additionally, metadata is part of the intents and in this case is used to define the language of the examples used since the chatbot is multilingual. The NLU file, therefore, is used to identify the intent from the user’s message, based on the examples provided in the intent grouping.

The stories file includes the name of the story, specifies the intents and actions as a list of steps to be followed in the conversation (Rasa Documentation, 2024). Stories, therefore, define the Dialogue Management section and train the model to understand the patterns followed in conversation and aid in the generalization for conversation paths which are unseen. Within the stories, checkpoints are also defined to determine the direction a conversation should take (Rasa Documentation, 2024). The stories, therefore, represent the chatbot’s conversation with the user in the format of intents describing the input of user while the actions define the chatbot’s response.

Consequently, the rules file trains the Dialogue Management component and are utilized for handling of specific conversations. They do not generalize unseen conversation paths similar to stories but they describe short conversation pieces (Rasa Documentation, 2024). As opposed to stories which are viewed as an example for the chatbot model to learn from, rules indicate a conversation pattern which the model must adhere to. Concurrently, rules include intents and the respective actions assigned to them.

Additionally, the other significant file in the Rasa components is the Domain file. The domain file is a specification of all intents, responses, session configuration and actions around which the chatbot model operates around (Rasa Documentation, 2024). It lists all intents highlighted in the NLU file then lists the responses associated with them since these are what the chatbot uses to respond to user input. All actions including custom actions to be utilized for response generation must also be defined in the domain file to inform the model’s functioning after receiving input from a user and identifying the intents using the NLU file. The actions define how responses will be generated and what criteria is to be used for selection of a response such random response selection based on fuzzy matching scores determined by comparison with the user’s input or generation of dynamic responses from the responses listed per intent. Furthermore, in the domain file, the logic of what to do if the model does not understand a user’s input is defined in the form of fallback action by checking if the NLU Confidence level

is below 50% (Rasa Documentation, 2024). In the domain file, these actions are only listed but their full definition is included in the actions file. The domain file is also the section outlining the time of session expiration and whether slots are to be carried over to a new session.

The Configuration file is where the model's policies and components are defined. In this section, the chatbot's identification is defined, the language as well is defined and can be either of the languages supported by Rasa Framework (Rasa Documentation, 2024). In this study, this can either be English or Kiswahili which are both supported but since the developed chatbot is a single-multilingual model, language is defined as "multilingual". The configuration file additionally specifies pipelines of the model's operation such as the threshold levels of the fall-back and DIET classifiers and response selectors.

5.2.2 The Web application

A Web application is used as the interface for users to interact with the chatbot that was developed using HTML and CSS for the front end and JavaScript for the backend logic including linking the web application to the Rasa Chatbot model using an endpoint. On the home page, it has a section where users type a message and another section where the response generated by the chatbot is displayed. Within the web page there is also a navigation pane which includes referrals to Kenya's agencies responsible for responding to different types of GBV cases. The referrals section is a link to another page of the web application where a user finds listed agencies in Kenya and their contacts including hotlines where a victim of GBV accesses assistance. Furthermore, the home page of the web application has a link to another page where mental, physical and soothing grounding exercises recommended for GBV victims are outlined (Mental Health and Psychosocial Support Minimum Service Package, 2023). The web page including the section to type a message and display the generated response in addition to the navigation pane with links to recommended grounding exercises and referral services within Kenya is as illustrated in the figure below.

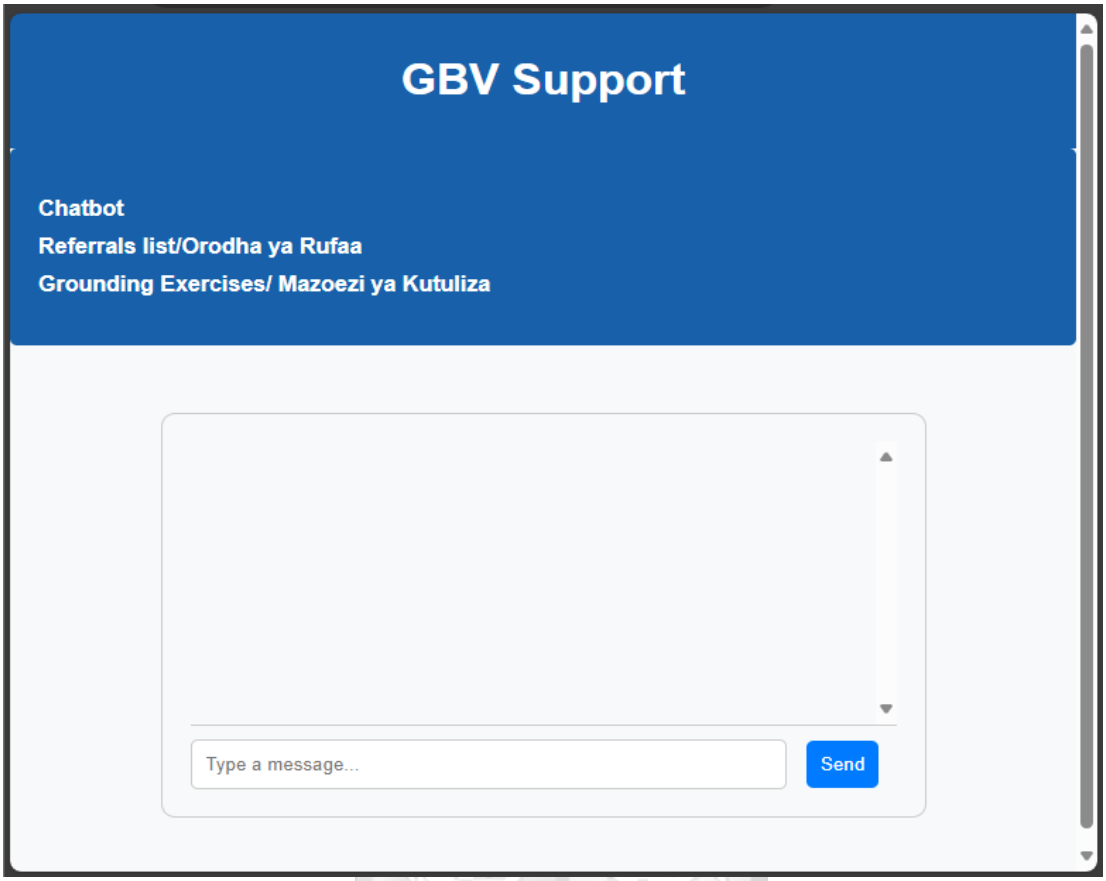


Figure 5.1: Web Application Chatbot Section

5.3 Implementation of the Chatbot Application

The development of the chatbot followed the sprints in Appendix 1. There were 5 sprints with the first being the data pre-processing and multilingual integration, the second involving implementation of the user input and intent recognition capabilities, the third sprint covering information retrieval and response generation, the fourth sprint entailing testing and preparation for deployment and finally, the fifth sprint covering user interface development and chatbot deployment. These were the 5 sprints utilized for coming up with the chatbot. Consequently, the approach of Separation of Concerns principle where a unique functionality or task is handled by a section of the code hence having segmented code blocks was utilized in the implementation of the chatbot application (Valderas, Torres, & Serral, 2023).

5.3.1 The Development Environment

The environment used for the implementation and testing of the chatbot utilized the following hardware and software:

i. HP Probook 440 14inch G9 Notebook PC
ii. Processor: 12th Gen Intel(R) Core (TM) i5-1235U, 1.30 GHz
iii. Installed RAM: 8.00 GB (7.64 GB usable)
iv. 500GB Hard disk
v. System type: 64-bit operating system, x64-based processor
vi. Windows 11 Pro Edition, Version 23H2
vii. Microsoft Visual Studio Code
viii. Python 3.11.5 in the global environment
ix. Python 3.8 within the conda environment
x. Miniconda 3
xi. Pandas and Numpy libraries
xii. Rasa 3.6.16
xiii. HTML, CSS, Javascript for Web application development

5.3.2 Data Pre-processing and Multilingual Integration

5.3.2.1 Multilingual Integration

For the translation of the dataset from English to Swahili, Google Translate was utilized because it supports uploading of .docx, .pdf, .pptx and .xlsx file types. At first, different methods were explored but they posed some challenges. In exploring translation tools for the data set which was in .csv format, integrating the Google Cloud Translate API into a Python script was considered. However, the Google Translate API operates on a pay-per-use model, and its free tier limits translations to 5000 characters. Beyond this limit, additional charges apply. This was done by using the following python commands for translation of 6 columns using the Google Translate API by creating a Google Cloud Project, enabling of the Google Cloud Translation API for this project, creating a service account and downloading the JSON key file which has its credentials then installation of the Google Cloud Translate library. The next steps involved setting up of a translation client, the target language then specifying which row and column to translate. Therefore, using this method was time consuming because it involved reading each row from the CSV, translating the specified column using the API then

adding the translated text to a new row in the output file. Additionally, the Microsoft Translator within Microsoft Office Word was explored. However, this approach necessitated converting the CSV file into Word format or manually copying and pasting each row and column into a word document. Furthermore, it encountered difficulties when translating data presented within a table structure which is the format of the dataset for this study.

Google Translated was, therefore, considered the most suitable option. A study on the challenges of English to Swahili conversational data translation using Computer Assisted means which focused on the Google Translate case indicated that despite the myriads of challenges, Google Translate is still a powerful tool for machine translation of sentences, phrases and words as opposed to translating conversational implicatures (Chacha & Iribemwangi, 2023). In addition, the study concluded that to ensure accuracy and quality of translation using tools of Computer Assisted Translation, post-editing is to be carried out by human translators to ensure that the meaning of the translated text is conveyed naturally and accurately (Chacha & Iribemwangi, 2023). Accordingly, once the dataset file type was converted from .csv to .xlsx, which is a supported format, then was uploaded to the Google Translate page for translation, the translated version was obtained by downloading it from the platform. For quality control of the output, the obtained Swahili dataset was reviewed by both the principle researcher and the dissertation supervisor to remove some of the errors in translation identified such as direct translation of metaphors and jargons hence losing the contextual meaning. After correction of the identified errors and ascertaining that the translation quality was sufficient, the English and Swahili datasets were combined to have the corresponding language versions aligned. A final check was then conducted.

Due to the need for creation of a chatbot which can converse in both English and Kiswahili, part of the multilingual integration was making the decision on the approach to take in the model training. One option was to create a single multilingual model where the model is trained with data in both English and Kiswahili languages combined with defined language metadata within the same model. The other option was developing multiple language-specific models where 2 separate models are trained using English data for the English model and Kiswahili data for the Kiswahili model, each with an endpoint, then utilize a hosting service with language detection capabilities to determine which model to be used for responding based on the user's input language.

A comparison was made on the advantages and disadvantages of both options before arriving at a decision. The table below outlines the considerations made.

Single Multilingual Model	**2 Separate Language-specific Models:**
Advantages	
Simplicity: Managing a single model is simpler than managing multiple models as it only requires training of one model. The data is organized in a single file, allowing for easy management and training of a single multilingual model. It also simplifies the deployment process as it only requires integration and management of one model on the web page.	Language-specific Optimization: Each model can be optimized independently for its respective language, potentially leading to better performance and accuracy.
Unified Experience: Users interacting with the chatbot don't need to switch between different endpoints or APIs based on language hence encountering a seamless user experience	Clear Separation and Maintenance: Keeping models separate provides clearer boundaries and organization, making it easier to manage and maintain, especially if updates or modifications are needed for specific languages.
Challenges	
Complexity of Data: Handling multiple languages within a single model requires careful and complex organization and annotation of training data to ensure effective learning and understanding across languages. Data must be properly labeled with the language context for each example. This allows the model to learn effectively across languages and provide accurate predictions for user inputs in different languages.	Deployment: Managing multiple models requires additional infrastructure and deployment considerations, such as separate endpoints for each language. Language-specific optimizations tailored to each user's language are required.

Language-specific Performance: The performance of the chatbot may vary across languages, depending on the quality and quantity of training data available for each language.	Coordination: Coordination between multiple models must be set up to include tasks such as language detection or routing user queries to the appropriate model which necessitates further setting up for the chatbot to function appropriately in each language.

Table 5.1: Single Multilingual compared to Multiple Language-Specific Model

The single multilingual model was selected because of the subject of the chatbot being GBV counselling hence the user experience is key (Rasave & Patil, 2021). Additionally, the challenges with the single multilingual model have workable solutions which involve ensuring proper, although complex, organization and labelling of the data to ensure both the English and Kiswahili languages are sufficiently covered in the training datasets.

5.3.1.2 Data Pre-processing

After this multilingual integration, the dataset was converted from .xlsx to .csv for pre-processing using python commands and the Pandas library. Within the same folder, a python file for the pre-processing source code was created and the dataset saved. The commands *import pandas as pd* imported the pandas library with the alias pd which is the library utilized for analysis and manipulation of data. A function *'def preprocessing()'* was then created to read the .csv dataset file, drop unnecessary columns, check for missing values, convert the text to lower case, return the resulting data and display it for verification and save this into a .csv file type.

data = pd.read_csv('dataset.csv', encoding = 'unicode_escape')

This command read the .csv file labelled 'dataset' into a dataframe in pand labelled 'data' and used the 'unicode_escape' parameter for handling of any special characters existing within the .csv file.

data.isnull().values.any()

This command was used to check for missing values within the dataframe.

data[column] = data[column].apply(lambda x: x.lower())

This command was used to convert the values in all columns to lowercase.

data[column] = data[column].apply(lambda x: x.replace("\r", "\n"))

This command was used to convert Carriage Return to Line Feed where character CR moves a cursor to the liné's beginning while the character LF moves a cursor into the next line.

data["topic"] = data["topic"].apply(lambda x: x.replace("-", "_"))

This command was used to replace - with _ for uniformity

special_characters =['"', "• ", "\x98", "\x93", "\x94", "\x9a", ":"]

for special_character in special_characters:

data[column] = data[column].apply(lambda x: x.replace(special_character, ""))

This command was used to remove special characters which were highlighted during the process of running the code.

The rest of the cleaning process was conducted by removing duplicates and dropping of unnecessary columns based on whether the training data is for NLU, stories, domain or rules file.

The pre-processing of the NLU, Domain, Stories, Rules files was conducted using different source code files because the different Rasa files' training data required to be generated using different sets of columns of the available counselling dataset following the Separation of Concerns principle. Furthermore, the program is not aligned in a single and linear interaction chain hence the sub-packages for each function were used to make the code easier to track, read and maintain.

In the pre-processing for NLU, the following command was used to keep only the necessary columns.

data = data[["question_title", "topic", "question_title_translated", "topic_translated"]]

This dropped the rest of the columns because for the NLU file because from the dataset, the "topic" and it's translation were utilized as the intent name in English and Kiswahili respectively. This is because in the conversation between the licensed therapist and the user, the query was grouped under specific topics such as "Domestic Violence", "Family Conflict" which were deemed suitable for creation of groupings which the chatbot's Natural Language Understanding could use as the intent name. Further, the "question_title" and its translation in the dataset are columns which describe the questions asked by the user which fall under a

specific topic and in the NLU file were utilized as examples in English and Kiswahili, respectively, for the intents defined.

In the pre-processing for domain, the following command was used to keep only the necessary columns.

data = data[["topic", "answer_text", "answer_text_translated"]]

This dropped the rest of the columns because from the dataset, the “answer_text” is the column containing the therapist’s response to the question by the user while “answer_text_translated” is the translated version. Therefore, for the domain file, these answer texts in English and Kiswahili were outlined under an intent originating from the “topic” under the “responses” component of the domain file.

In the pre-processing for stories and rules files, the following commands were used to keep only the necessary columns.

data = data[['topic','topic_translated']]

This dropped the rest of the columns because from the dataset, the grouping represented by the “topic” column and its translation were the only columns needed for the stories and rules files which utilize the intent from the “topic” and their translation entries in addition to defining an action for each intent.

For all pre-processing source codes for the 4 distinct files, the following command was included in the respective segment.

data.to_csv("dataset_new_domain.csv", index = False)

data.to_csv("dataset_new_nlu.csv", index = False)

data.to_csv("dataset_new_rules.csv", index = False)

data.to_csv('dataset_new_stories.csv', index = False)

This command converted the resulting data within the dataframe into a new .csv file excluding the index column. The obtained dataset was then clean for annotation and conversion to a Rasa acceptable format, YAML, for the modification of the NLU, domain, stories and rules files within the Rasa project. The pre-processing source codes for the 4 files are contained in Appendix 3.

5.3.2.3 Data Conversion to YAML format

The next step was to convert the obtained datasets for the 4 distinct files into the YAML format which is the required format for feeding into the NLU, Domain, rules and stories files in the Rasa model. The conversion for each of the 4 files was done separately because of the different components required by the distinct files. For the domain and NLU files, default responses that include the beginning and end of the conversations such as greetings, bidding goodbye and queries about whether this was a human or bot interaction, which are not included in the counselling dataset, were added to ensure proper dialogue between the user and the chatbot application as per the guidelines of a psychotherapy session as provided by relevant organizations (Mental Health and Psychosocial Support Minimum Service Package, 2023).

The commands for conversion of the preprocessed dataset in CSV format to the domain, NLU, stories and rules files in YAML format is as per the source code segments in Appendix 3**.** The resulting YAML file for the NLU file appears as in the figure below.

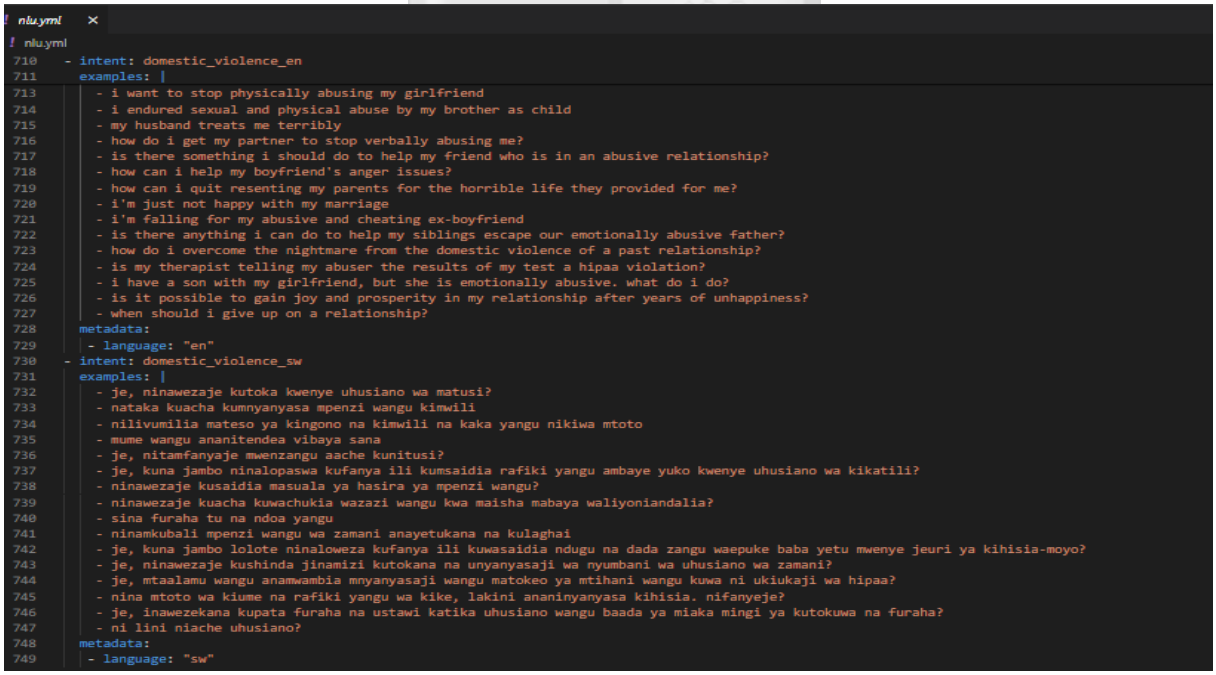


Figure 5.2: NLU file content format

The resulting YAML file for the domain file appears as in the figure below.

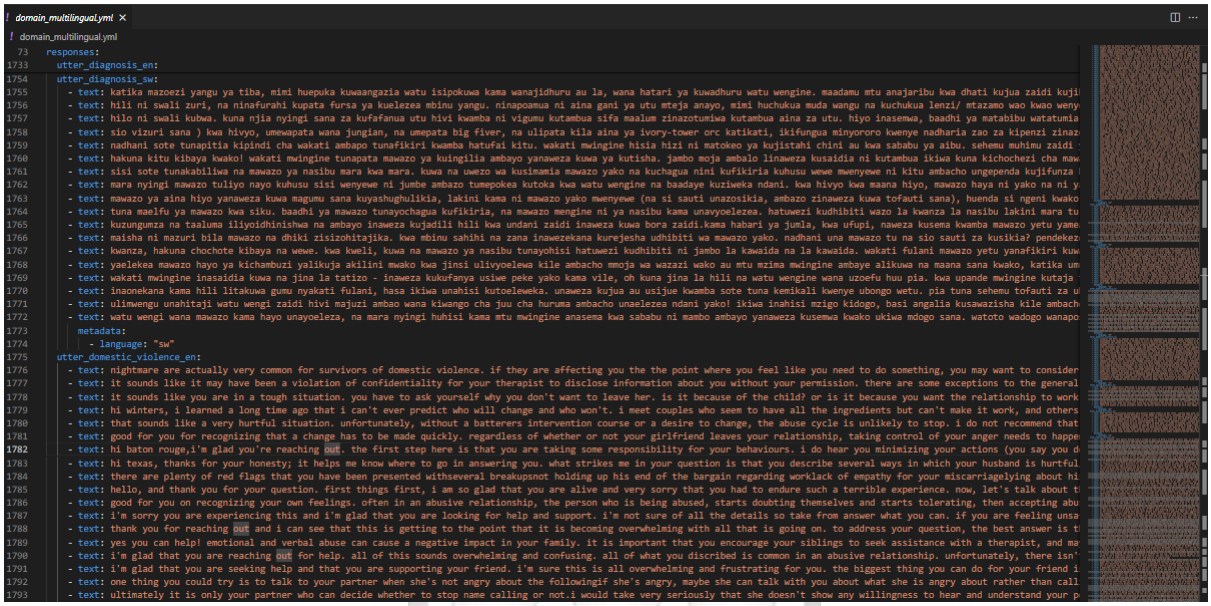


Figure 5.3: Domain File Content Format

The resulting YAML file for the rules file appears as in the figure below.

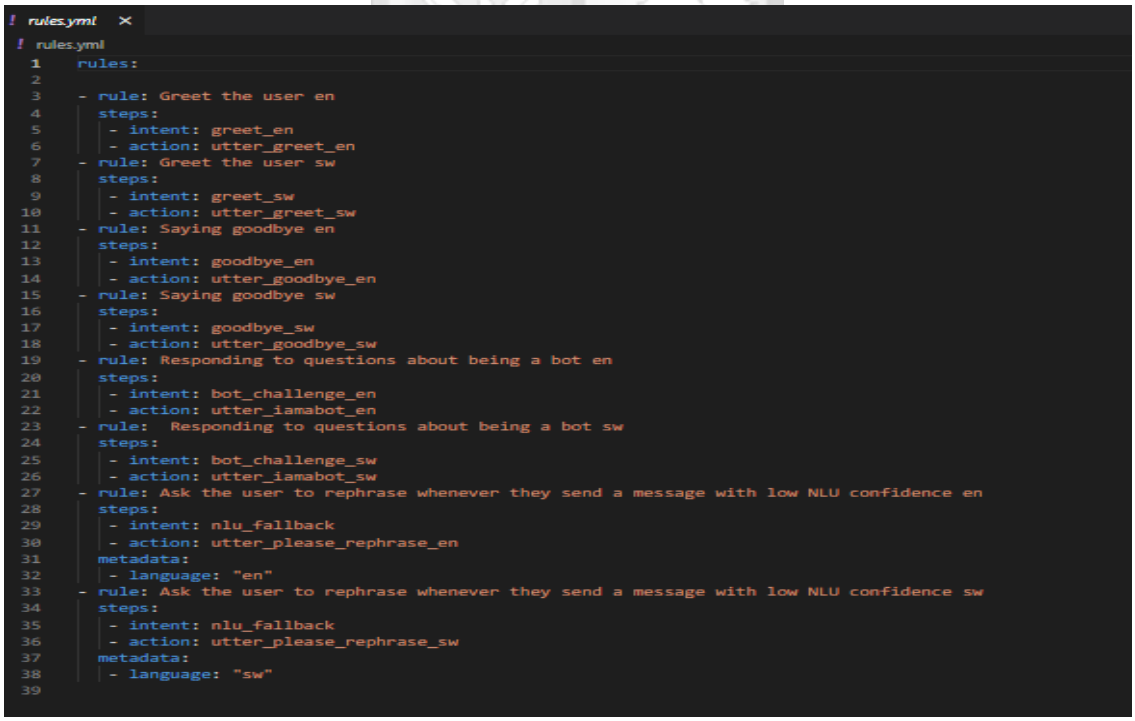


Figure 5.4: Rules File Content Format

The resulting YAML file for the stories file appears as in the figure below.

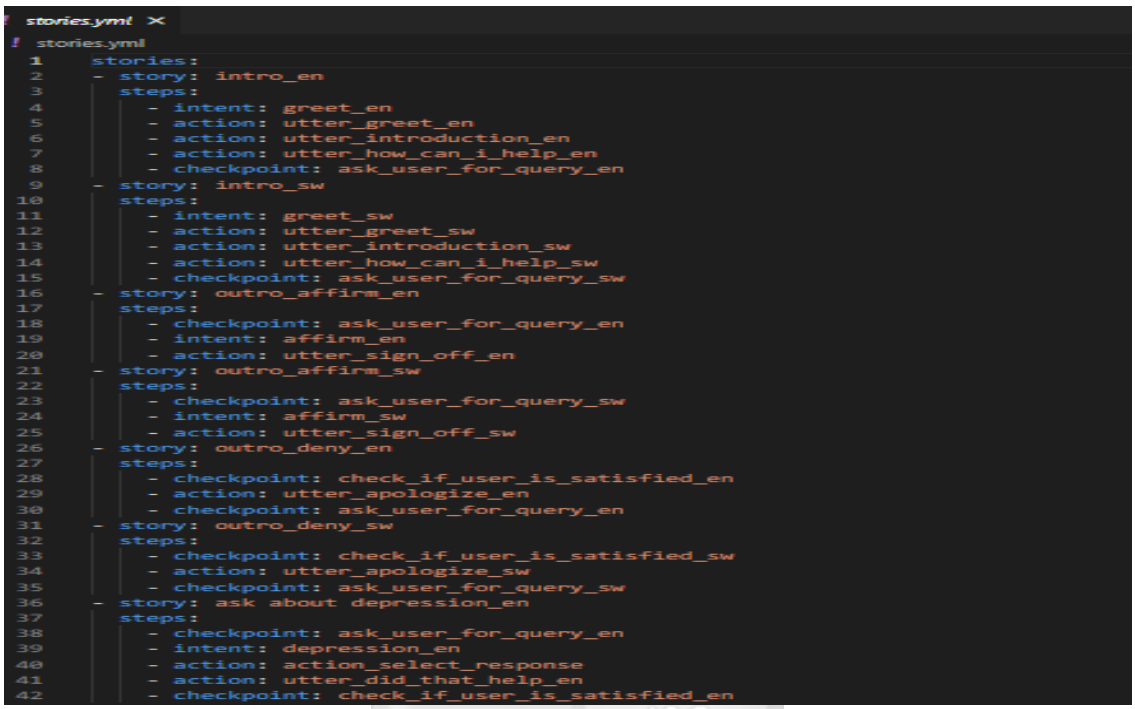


Figure 5.5: Stories File Content Format

5.3.3 Model Training and Evaluation

This involves set up and testing of the model where the following were installed and tested as part of the development process.

5.3.3.1 Miniconda

This is the minimal and lightweight installer for conda. Conda is a package and environment manager which is needed for managing the python environment. Rasa documentation requires anaconda but when installed gave a storage error due to limited disk space. This is because Anaconda requires around 3 GB of disk space for installation because it includes more than 1500 pre-installed packages. Miniconda requires approximately 400 MB of disk space because it only installs conda and python, in addition to the essential packages required for basic functionality of conda and python. Miniconda then allows you to install the packages needed using the command “conda install ‘numpy’” with numpy as an example of a package. This reduces the clutter in the computer.

The essential packages bundled together with python and conda for their basic functionality include:

Package	**Function**
Pip	Python package installer
Setuptools	A library for facilitation of python projects packaging
Wheel	Python's built-package format for speeding up the installation of especially packages with binary extensions
Requests	A HTTP library which makes HTTP requests in Python
Pyyaml	Python's YAML (Yet Another Markup Language) parser and emitter. • YAML is a human-readable data serialization language that is often used for writing configuration files • Emitter- takes a sequence of events and produces a stream of bytes The emitter appens strings together while following along the parse tree. • The parser takes an input stream of bytes and produces a sequence of parsing events.
certifi	A Python package which provides Mozilla's CA bundle for SSL/TLS certificate verification and is used for ensuring secure HTTP requests.
urllib3	A python HTTP client used in combination with requests for making HTTP requests.
Conda-build	For the building of conda packages from recipes.
Conda-env	A package to allow users to create, export and import conda environments as part of managing them.
Conda-package-handling	A library used to provide programmatic interfaces to work with conda packages, creation and extraction of the packages.

Table 5.2: Miniconda Packages for Chatbot Application Developement

5.3.3.2 Rasa Open Source

Rasa Open source was then installed using the following commands on the Command Line Interface.

conda create --name WAIRIMU python==3.8

This created a new Conda environment called WAIRIMU which utilizes Python version 3.8 installed together with miniconda. The conda environment is an isolated environment whose

package installation does not affect other environments. The Python version is specified because the global operating system has a different and the latest version of Python (3.12) which is not compatible with the Rasa open source installations.

conda activate WAIRIMU

This activated the newly created environment, therefore, the subsequent commands run within this environment. Therefore, succeeding package installations remain within the new environment.

python -m pip uninstall pip

This command uninstalled the pre-installed 'pip' package. This is required so that a clean installation of 'pip' is carried out.

python -m ensurepip

This ensured that there is presence of 'pip' package within the python environment. '-m' is a flag which stands for module.

python -m pip install -U pip

Using the '-U' (A flag which stands for Upgrade) commands installation of the latest version of 'pip' package.

pip install rasa

Using the just upgraded 'pip', this command installed the Rasa package. This is the package essential for building this chatbot application.

rasa -h

To confirm that Rasa is installed, the following command for invocation of the Rasa tool is used. This command displays information about the Rasa CLI tool in addition to listing available commands and their descriptions. If Rasa is not installed, an error message is displayed indicating "command not found". The following was displayed as per the figure below.

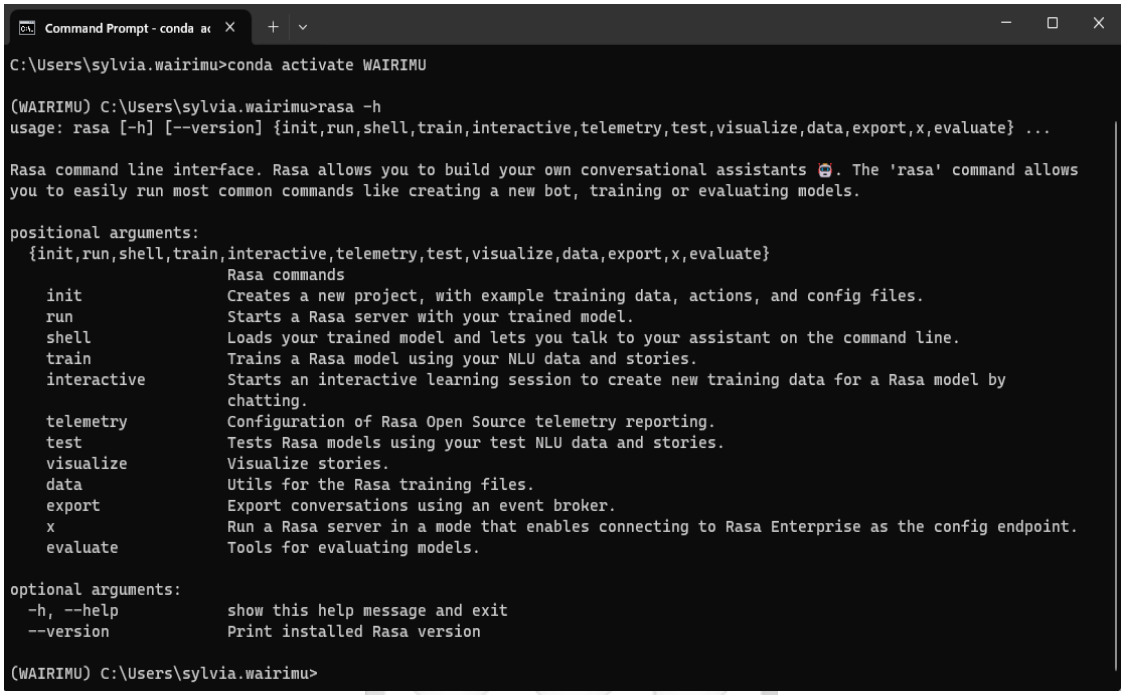


Figure 5.6: "rasa -h" Command Output

rasa init

The next step was then to initialize rasa using the command 'rasa init'. This initializes a new Rasa project by creating a directory structure where all the require files and folders are set up to act as the root of this project. Running this command created the necessary configuration files for the configuration of core and NLU components in addition to the files for definition of chatbot domain. These files include 'config.yml' for core and configuration and the 'domain,yml' which contains defined responses, intents, entities, rules and actions. A Git repository was also created during initialization.

These were the files created on running 'rasa init'

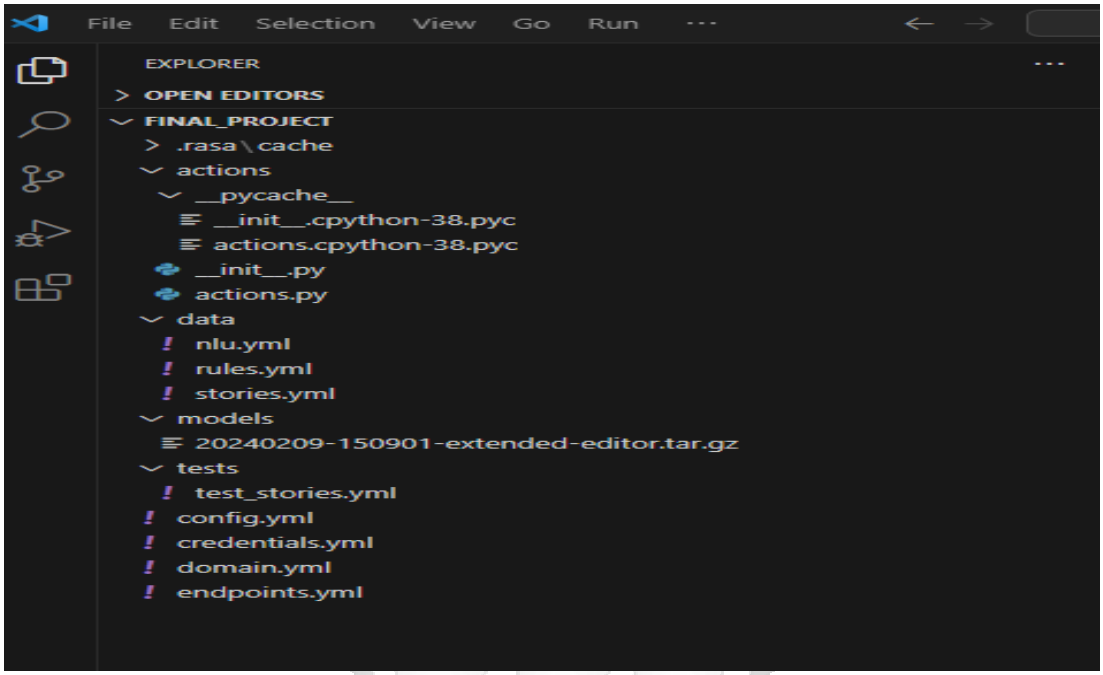


Figure 5.7: Rasa Project Files Format

rasa run

The succeeding command was rasa run which is used to start a local Rasa HTTP server for the provision of an interface to interact with the trained model through REST API endpoints by listening for incoming requests, handling these requests then responding based on predictions derived from the trained model. Port 5005 is used by Rasa with the option of specifying a varied port based on need. On receiving a request, the server processes it by comprehending the input's intent and extraction of entities after which the server returns predicted entities, intents, actions and associated responses in JSON format. Subsequently, after responding, the server continuously listens for requests which are incoming to ensure that a client has a real-time interaction with the chatbot. This local server the enabler of the chatbot's integration into varied applications and platforms by sending the HTTP requests to the server and, accordingly, receiving JSON format responses.

rasa shell

rasa shell command was then run to create a simulated chat environment which allows direct interaction with the trained model from the command line by starting an interactive session for evaluation of the chatbot's behavior so far. In this shell, the model requests an input and once a message is typed, the NLU component of Rasa processes it to identify intent and entities in the message. Consequently, based on the understanding from the input and consideration of

the conversation history, the dialogue management component determines the response. Rasa shell then displays the response and requests for another input because it is set up for multiple entries. The following was displayed on running ‘rasa shell’ and interacting with the chatbot.

```
2024-02-13 12:27:53 INFO     root  - Connecting to channel 'cmdline' which was specified by the '--connector' argument. Any other channels will be ig
nored. To connect to all given channels, omit the '--connector' argument.
2024-02-13 12:27:53 INFO     root  - Starting Rasa server on http://0.0.0.0:5005
2024-02-13 12:27:53 INFO     rasa.core.processor  - Loading model models\20240209-150901-extended-editor.tar.gz...
2024-02-13 12:28:08 WARNING  rasa.shared.utils.common  - The UnexpecTED Intent Policy is currently experimental and might change or be removed in the
 future 🔬 Please share your feedback on it in the forum (https://forum.rasa.com) to help us make this feature ready for production.
2024-02-13 12:28:14 INFO     root  - Rasa server is up and running.
Bot loaded. Type a message and press enter (use '/stop' to exit):
Your input ->  hello
Hey! How are you?
Your input ->  fine
Your input ->  how are you
I am a bot, powered by Rasa.
Your input ->  okay bye
Bye
Your input ->
```

Figure 5.8: Greeting Interaction in English

This interaction demonstrated that the behavior of the chatbot so far was appropriate using English language.

The same interaction was tested using Swahili by replacing the English examples of intents ‘greet’ and ‘goodbye’ in the nlu.yml file as below. The configuration file was also updated to reflect ‘multilingual’ instead of being specific to English or Kiswahili since out chatbot would be trained to interact with both.

```
final_project
nlu.yml
data > nlu.yml
1   version: "3.1"
2
3   nlu:
4   - intent: greet
5     examples: |
6       - Habari
7       - Hujambo
8       - Sasa?
9       - Habari ya leo
10
11  - intent: goodbye
12    examples: |
13      - Kwaheri
14      - Tutaonana baadaye
15      - Tuonane
16
```

Figure 5.9: NLU File in Kiswahili

The domain file was also edited to include Kiswahili responses as shown below.

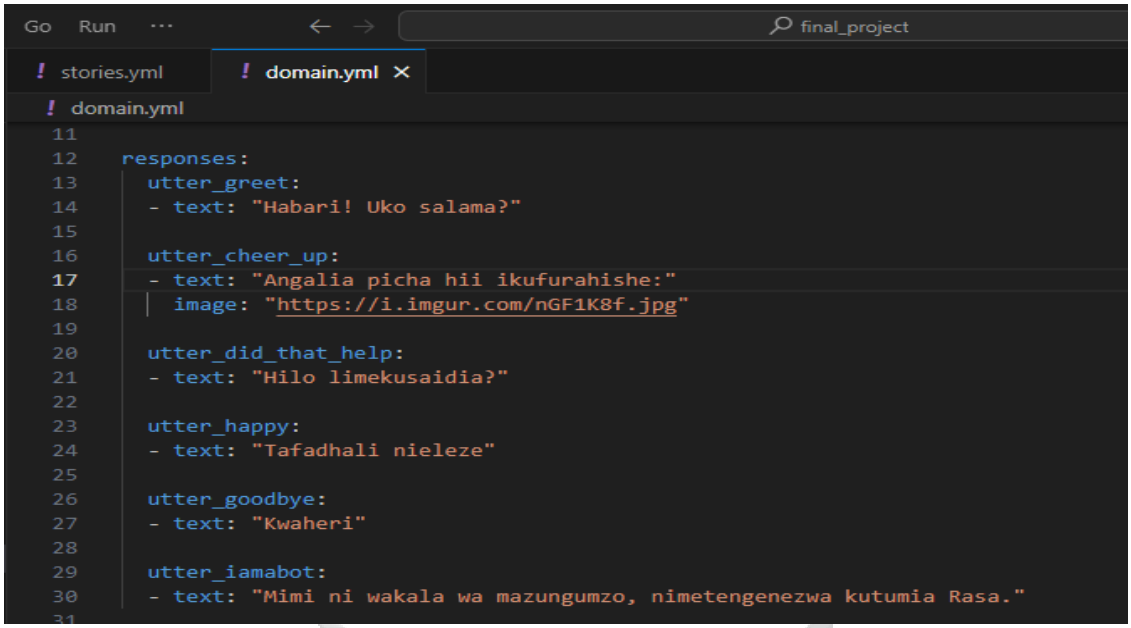


Figure 5.10: Domain File in Kiswahili

After replacing the English examples with Kiswahili ones, the command to re-train the model using the updated data was used. This is the result of the command ‘rasa train’ which also checks that the data was accepted.

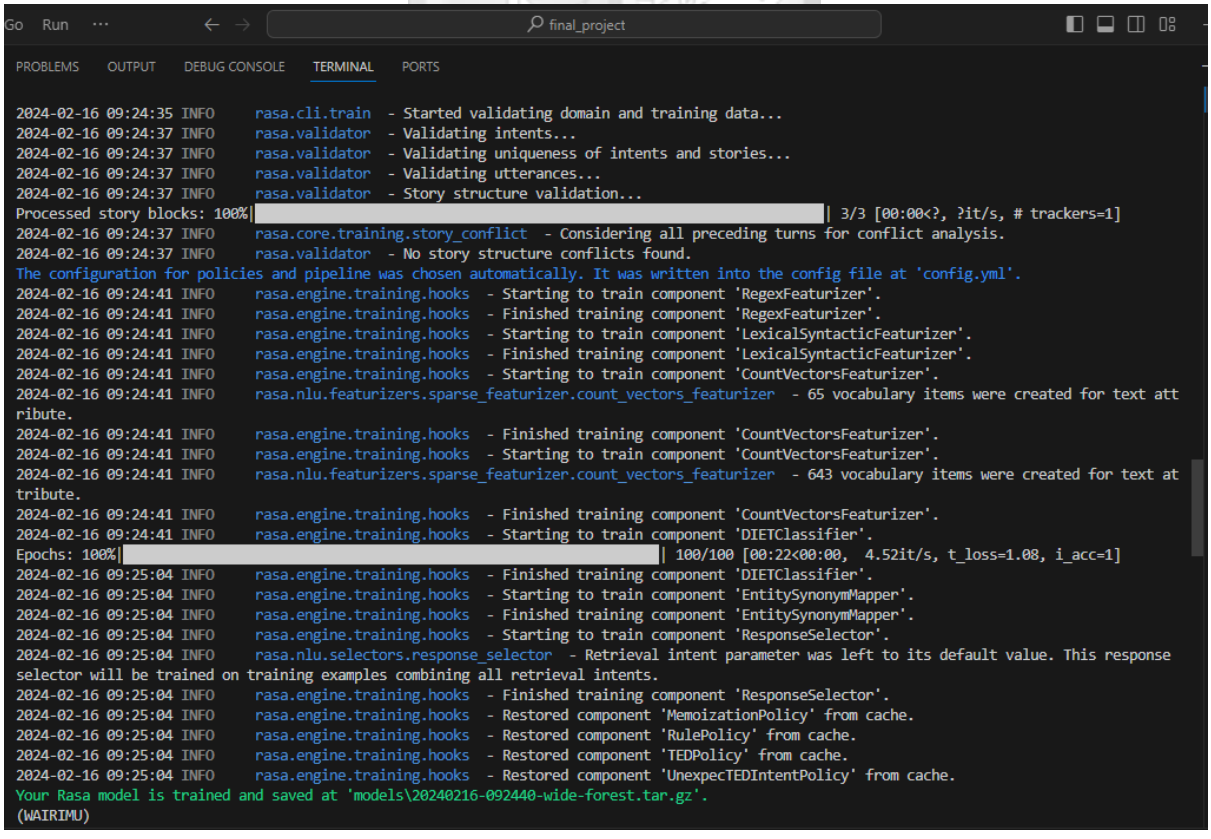


Figure 5.11: Training of a Chatbot Model

On interacting with the model in Swahili using the ‘rasa shell’ command, in Swahili, the following was generated.

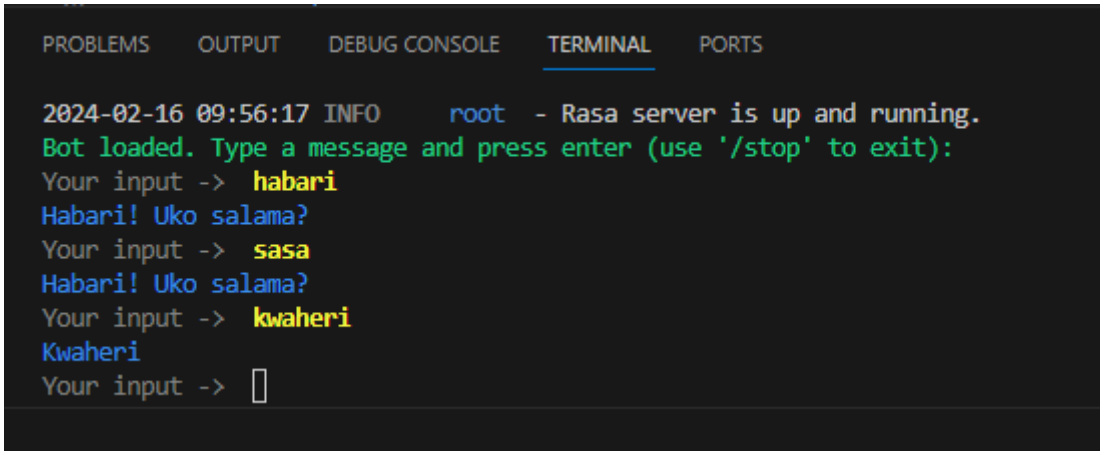


Figure 5.12: Greeting Interaction in English

The model is, therefore, able to receive input and respond in Swahili using the pre-programmed examples.

5.3.4 Model Training using the Pre-processed Data Files

This step was implemented by subjecting the chatbot model with the training data from the counselling dataset for the 4 distinct files to enable the chatbot to respond appropriately to user input in the counselling context hence enhancing the intent identification and selected responses. This was done by replacing the pre-programmed NLU, Stories, Rules and Domain files in the Created Rasa chatbot project with the pre-processed training data files in YAML format. Additionally, the configuration file was edited to indicate the language as “Multilingual” and not English or Kiswahili since the model being developed would be trained with data in both languages to enable bilingual conversation. If one language was specified, the chatbot would only be able to recognize and process inputs in that language and fail to understand inputs in a different language.

After the replacement of the files, automated splitting of the dataset by Rasa Framework was used to create a test set for evaluation of the model performance in terms of NLU accuracy of intent classification by using a command “rasa data split nlu” (Rasa Documentation, 2024; White , 2020). This command withholds a test set from the training data utilized in training a model hence the test set is used at a later stage as a benchmark of evaluation of the model’s generalization. The command split the data in an 80% for training and 20% for testing. Accordingly, in the development of the model, the split command was utilized, after which the “rasa train” command was implemented to train the model. “rasa train” was used to instruct the

model to train using the updated data. After processing for about 40 minutes, the model indicated processing error which involved the presence of a special character. This special character was included in the data pre-processing files for removal from the 4 files. The training process was then repeated about 5 times, each time indicating a different special character and every time the character would be removed by adding it to the list of characters to be removed from the training data then repeating the retraining cycle again. These characters detected at this training stage had not been removed earlier in the pre-processing stage because previous works and Rasa Documentation had not indicated them on the list of characters to look out and they occurred because they existed in the counselling dataset. After removing all the detected special characters, retraining was conducted and indicated as "successful" on the terminal. Further, the "rasa test nlu" command was to evaluate the model's NLU classification accuracy. A confusion matrix was generated by the testing command which is a grid which is a representation of the frequency that the model made a correct classification with the x-axis containing the model's predicted intent while the y-axis has the actual intent (Rasa Documentation, 2024; White , 2020). The confusion matrix indicated a 100% accuracy of intent classification based on the testing data.

5.3.5 Testing of the Chatbot Application Model with GBV Queries

The succeeding step involved utilizing the *"rasa interactive"* command which is an interactive session provided by Rasa to check the chatbot's logic step by step as shown in the figure below.

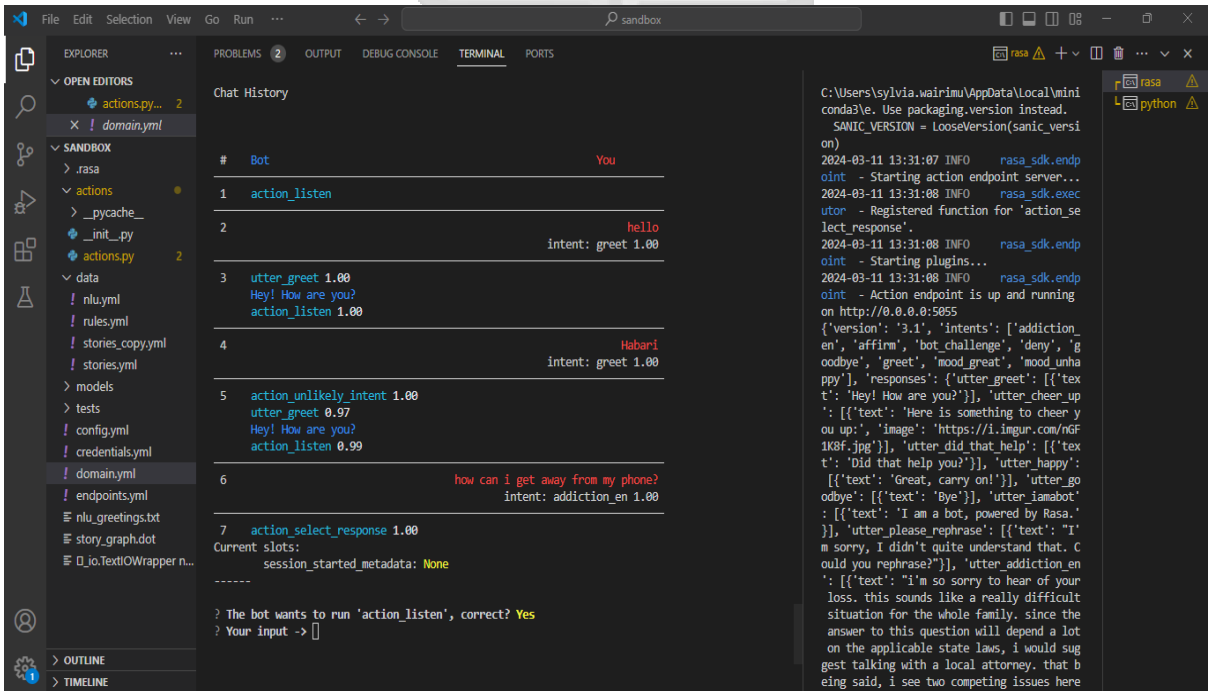


Figure 5.13: Interactive Session with the Trained Model

The step by step logic appeared appropriate but the interaction indicated a problem with the chatbot's response generation for a Kiswahili greeting. It was established that the handling of Kiswahili greetings had not been specified in the domain file. To correct this, the chatbot's domain and stories files were modified to include responses and actions for handling of conversation introduction and end in addition to querying about the chatbot's identity in both English and Kiswahili.

After this was handled, retraining was conducted using the *"rasa train"* command then to begin another interactive session, *"rasa shell"* was used to test other intents' response generation by providing inputs and viewing the generated response through the terminal. Snippets of the conversation are highlighted in the figures below.

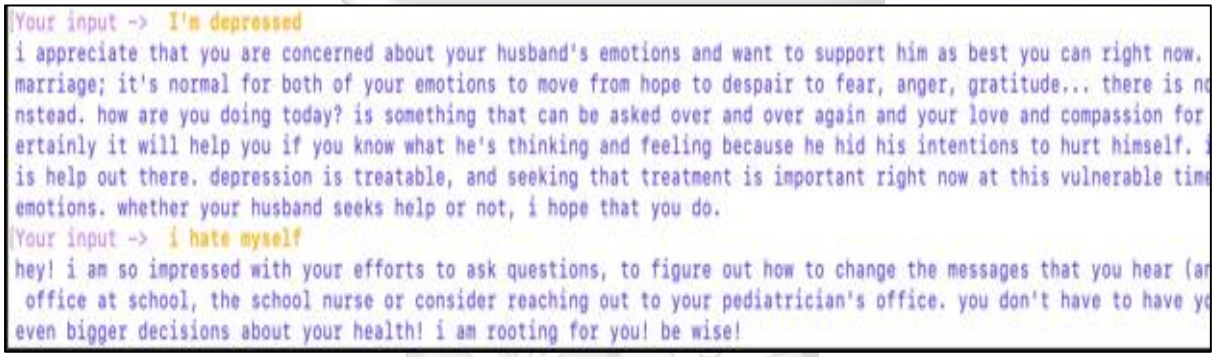


Figure 5.14: Generated Response Snippet 1

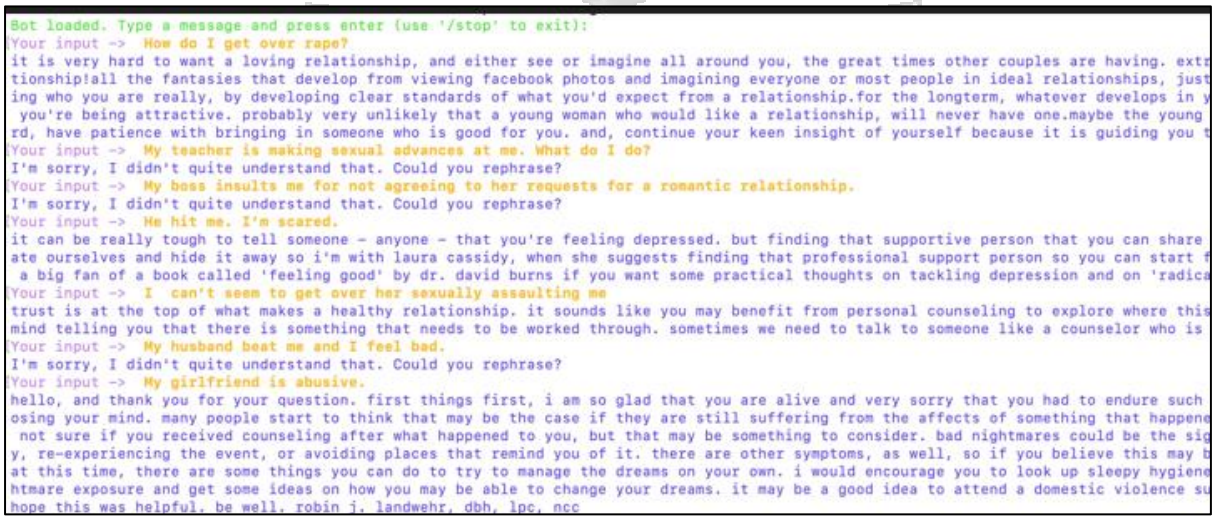


Figure 5.15: Generated Response Snippet 2

It was evident that the responses being generated were part of the domain file specified responses from the listed intents but they were unrelated to the input provided. On following

the logic of the decision-making process used by the chatbot model to arrive at these faulty responses using the "rasa interactive" command, it was noted that the model would identify an intent using the NLU module and mapped the intent to the domain file for response generation. However, the model would randomly select one of the listed examples of responses for the identified intent from the dataset's counsellors' answer to a patient's query without matching the input received to the most suitable response. Therefore, the criteria being used by the chatbot model was that as long as a response was listed under the identified intent's response list, it was a suitable response.

5.3.5.1 Response Enhancement

A fallback plan was included to ask for more information in the event that the NLU engine did not quite understand the query and was set at 50% confidence level for the questions asked. The NLU confidence level matches the input with the intents listed and matches the interaction to pick the most appropriate. The accuracy that the model determines that it has picked the correct intent is shown as a number which is a percentage and the highest number is picked as the best match hence the model determines that this is the intent where the user's input belongs. This NLU confidence computation is inbuilt in the Rasa open-source framework (Khojah, 2022). Accordingly, the fallback method provided by Rasa was linked to this NLU confidence level and was used to request further information when the score is below 50% hence helping the model not to crush each time an unfamiliar question is asked.

Further to addressing this response generation fault and to improve the responses provided, a different approach from the random picking of responses, therefore, needed to be applied to ensure that the model picked the most suitable responses. To address this, Rasa framework provides custom actions which were used in this case to refine the selection of a response to be more intelligent. Custom actions within Rasa framework are utilized for user-specific requirements of conducting of varied steps within a story such as querying databases, making API calls, adding events to a calendar and checking of a balance in a bank account in addition to myriads of other uses one wishes to incorporate into their model (Rasa Documentation, 2024).

Accordingly, inclusion of custom actions to further inform the chatbot model how to respond to queries better was conducted by including the custom action into the domain file as a specification of handling an identified intent's response generation then adding an actions file

into the Rasa actions component which defines exactly the functionality of the custom action by providing source code to instruct the model on how to handle a query. Therefore, at an instance where the dialogue engine has made a prediction that a custom action requires to be executed, the action server is called and responds as per the steps provided. The custom action utilized in this case was used to instruct the chatbot model to loop through all the responses of the identified intent and compare their fuzzy matching scores then pick the best response as the one with the highest matching.

The open-source FuzzyWuzzy library in python was used to conduct strings comparison between a query and the available responses in the identified intent to help in selection of the best response (Zhou, Nurkowski, Mosbach, Akroyd, & Kraft, 2021; Bozhilov, 2023). The FuzzyWuzzy library utilizes the Levenshtein distance for the calculation of differences existing between patterns in addition to sequences and has been utilized in different applications in conjunction with Natural Language Processing to enable the matching of sentences and phrases to specific terms being searched for (Tsili & Katsamanis, 2023).

This process of using custom actions involved creating a new python file within the actions section of the Rasa project called “actions”.The Fuzzywuzzy module was then imported which compares strings and returns a score between 0 and 100 in which case a score of 100 means that the strings are identical strings. The command used was:

from fuzzywuzzy import fuzz

For running of the custom action, the commands below were also included:

from typing import Any, Text, Dict, List
from rasa_sdk import Action, Tracker
from rasa_sdk.executor import CollectingDispatcher

Further, each custom action was then defined as a class as below.

```
class ActionSelectResponse(Action):

    def name(self) -> Text:

     return "action_select_response"
```

The name method was used to define what the custom action would be called across all the files.The run method was then used to define the steps to be followed when the custom action is called as illustrated below.

```
  def run(self, dispatcher: CollectingDispatcher, tracker: Tracker, domain: Dict[Text, Any]) -
> List[Dict[Text, Any]]:
    #Extracting the user's most recent input
    current_input = tracker.latest_message['text']
    #Identifying the intent and confidence
    current_intent = tracker.latest_message['intent']['name']
    confidence = tracker.latest_message['intent']['confidence']
    #Extracting the responses for the identified intent
    responses = []
    for response in domain['responses'][f'utter_{current_intent}']:
      responses.append(response['text'])
    #Finding the most appropriate response based on the current_statement
    scores = []
    for response in responses:
```

The algorithm called Token set ratio was determined to be the most accurate method for comparing the responses to the user's input. With Fuzzy string matching, varied ratios are available for conducting the comparison and they include Fuzz Ratio, Token Set Ratio, Fuzz Partial Ratio and Token Sort Ratio (Pankajakshan & Sridevi, 2020). This is because the algorithm called Fuzz Ratio checks the similarity of 2 strings by conducting a calculation of the single-character edits minimum number which includes insertions, substitutions and deletions which are required for the transformation of a string to the other with a score of 0-100 where 100 is an exact match (Zhang, et al., 2020). It is suitable for strings which may contain minor differences caused by spelling variations and typos. On the other hand, fuzz partial ration matches strings similar to fizz ration but also considers the substring that matches best and its score is based on the length of the substring which is longest and most common, as opposed to the entire string. It is most suitable for the handling of a string which is a prefix or a subset of the string being compared with to check the matching of a substring (Vitman, et al., 2022).

Token Set ratio was selected because it considers the content's essence for the string in consideration as opposed to the specific order since the score is a determination done by tokenizing of both strings, removal of duplicate tokens then bases the score on union and intersection of the sets of tokens (Vitman, et al., 2022). It is, therefore, suitable because it applies best in cases where the order and arrangement of words may vary but the content is

generally similar. Consequently, Token Sort Ratio algorithm operates by comparing strings in addition to making considerations on word order variations because it involves initially sorting the tokens in alphabetical order then conducting a similarity check rate considering fuzz ratio of the sorted lists of tokens. (Pankajakshan & Sridevi, 2020). Accordingly, Token Set Ratio which does not require to sort the strings first was selected as the most suitable.

The command line below was utilized.

scores.append(fuzz.token_set_ratio(response, current_input)

#Responding to the user

The next lines of code involved finding the response with the highest score and displaying it in addition to the printing the NLU confidence level indicating that the model is confident about the identified intent in addition to displaying the Fuzzy Matching score to indicate the Token Set Ratio score of the response selected.

dispatcher.utter_message(text = responses[scores.index(max(scores))])

dispatcher.utter_message(text = f'NLU Confidence - {confidence}')

dispatcher.utter_message(text = f'Fuzzy Matching Confidence - {max(scores)}')

return []

The full source code for this defined custom action is as the figure below.

```
from fuzzywuzzy import fuzz
from typing import Any, Text, Dict, List
from rasa_sdk import Action, Tracker
from rasa_sdk.executor import CollectingDispatcher


class ActionSelectResponse(Action):
  def name(self) -> Text:
    return "action_select_response"

  def run(self, dispatcher: CollectingDispatcher, tracker: Tracker, domain: Dict[Text, Any]) -
> List[Dict[Text, Any]]:
    #Defining the user's most recent input
```

```
current_input = tracker.latest_message['text']
#Identifying the intent and confidence
current_intent = tracker.latest_message['intent']['name']
confidence = tracker.latest_message['intent']['confidence']
#Extracting the responses for the identified intent
responses = []
for response in domain['responses'][f'utter_{current_intent}']:
  responses.append(response['text'])
#Finding the most appropriate response based on the current_statement
scores = []
for response in responses:
  scores.append(fuzz.token_set_ratio(response, current_input))
#Responding to the user
dispatcher.utter_message(text = responses[scores.index(max(scores))])
dispatcher.utter_message(text = f'NLU Confidence - {confidence}')

dispatcher.utter_message(text = f'Fuzzy Matching Confidence - max(scores)}')

return []
```

Figure 5.15: Custom Action Source Code

Subsequently, the domain file was modified to include a rephrase response action to the list which requests the user to rephrase their input if the NLU Confidence level that it picked the correct intent provides a score which falls below 50%. For further response enhancement and dialog management, the following modifications were included in addition to implementation of the custom action as per the table below.

Domain File	
Added default responses in both English and Kiswahili at the top of the domain file:	
1. Utter_ greet	To introduce the session with a greeting
2. Utter_ introduction	To tell the user that they are talking to a bot.
3. Utter_ how can I help	To ask for input after the introduction.
4. Utter_ did that help	To ask the user if they are satisfied.
5. Utter_ sign off	To sign off if the user is satisfied with the response.

6. Utter_ apologize	To apologize if the user is not satisfied with the response
7. Utter_ I am a bot	For bot challenges.
8. Utter_ please rephrase	For situations where NLU confidence is low (below 50%).
NLU File	
Added default responses in both English and Kiswahili at the top of the domain file:	
1. Greet.	Different examples of how the user can greet the chatbot
2. Goodbye	Different examples of how the user can say goodbye
3. Affirm/Deny	To allow the user to say whether or not they are satisfied with the response
4. Bot challenge	For bot challenges
Rules File	
Defined 3 rules in English and Kiswahili which must follow the same path every time.	
1. Saying goodbye.	
2. Responding to questions about being a bot.	
3. Asking a user to rephrase if NLU confidence is below the threshold.	
Stories File	
Defined 3 default stories.	
1. Introduction	a) The chatbot greets the user.
	b) The chatbot introduces itself.
	c) The chatbots enquires about how it can help.
	d) **Checkpoint** – A handover to the intent story is done by using the input from the user on how they need assistance then using the input to generate a suitable response. (see below).
2. Outro Affirm (good response):	a) **Checkpoint** - Handover from an intent story.
	b) The bot checks whether the user has affirmed or denied the previous question (Did that help you?).
	c) If the user is happy, sign off.
3. Outro Deny (bad response):	a) **Checkpoint** - Handover from an intent story.
	b) The bot checks whether the user has affirmed or denied the previous question (Did that help you?).
	c) If the user is not happy, apologize.

	d) **Checkpoint** - Handover to the intent story (see below) - This restarts the loop and the user can ask another question or rephrase.
The intent story: Each intent has this as a story using the for loop	
Defined the intent story.	a) Checkpoint - Handed over from either the intro or the outro deny story.
	b) Identify the intent of the question.
	c) Use the action_select_response custom action that we defined earlier.
	d) Ask the user whether the response was helpful.
	e) Checkpoint - Hand over to the outro story (affirm or deny).

Table 5.3: Response Enhancement Summary

The chatbot was then tested using Gender Based Violence related queries to check on the process of intent identification and response generation based on the custom action. This involves running the action server by the use of the rasa command "rasa run actions" and ensuring that it is up and running as in the image of the terminal below.

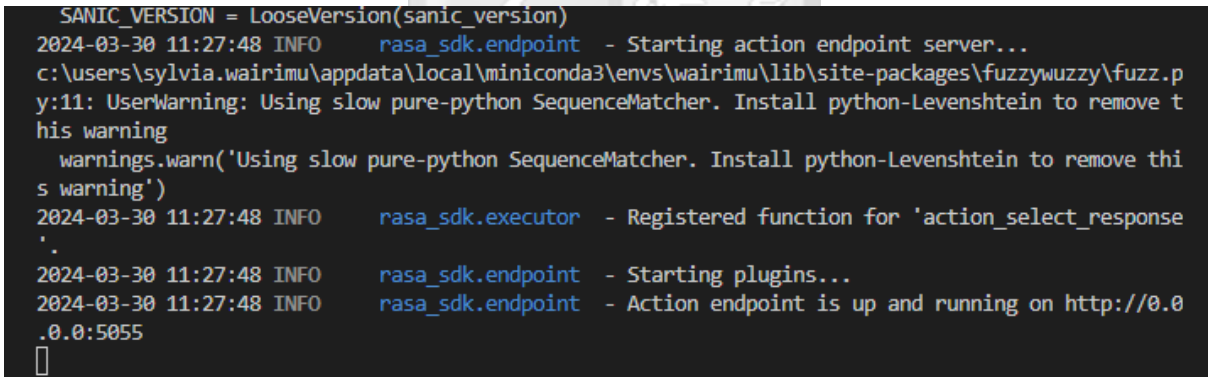


Figure 5.17: Running the Actions Server

Once the actions server is up and running, the next is to start an interactive session by the use of "rasa shell" or "rasa interactive" and providing an input so that the chatbot can identify intent and select a response based on the custom actions.

A sample of the query made is as below interaction with the chatbot. The confidence level of the responses is also displayed to indicate the NLU confidence that it identified the correct intent.

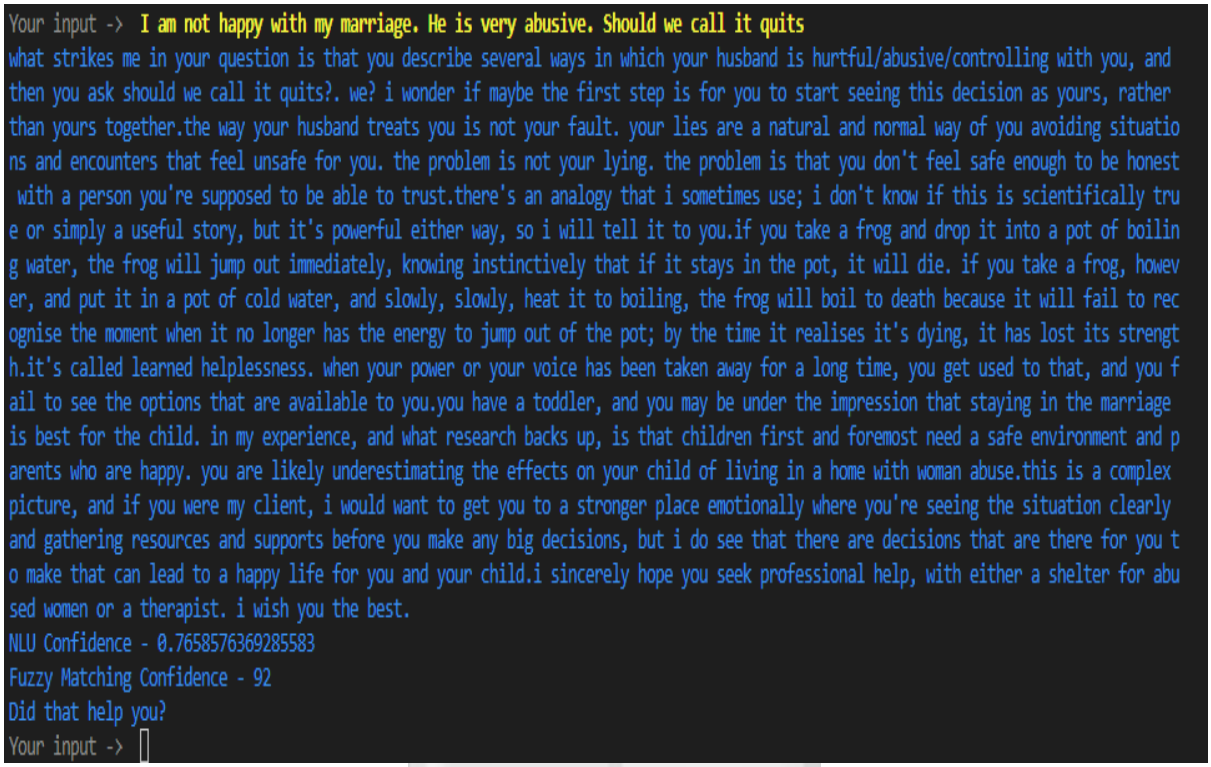


Figure 5.18: Conversation in English with 76% NLU confidence and 92% Fuzzy Matching

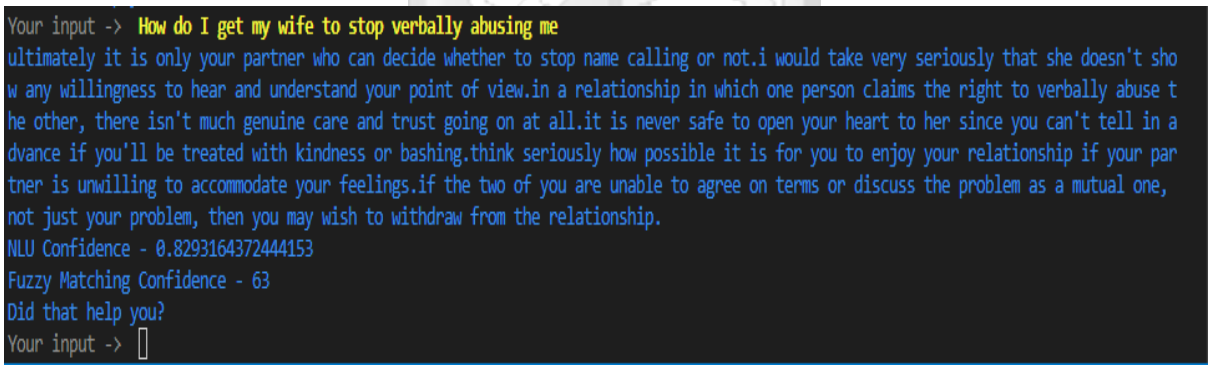


Figure 5.19: Conversation in English with 82% NLU confidence and 63% Fuzzy Matching

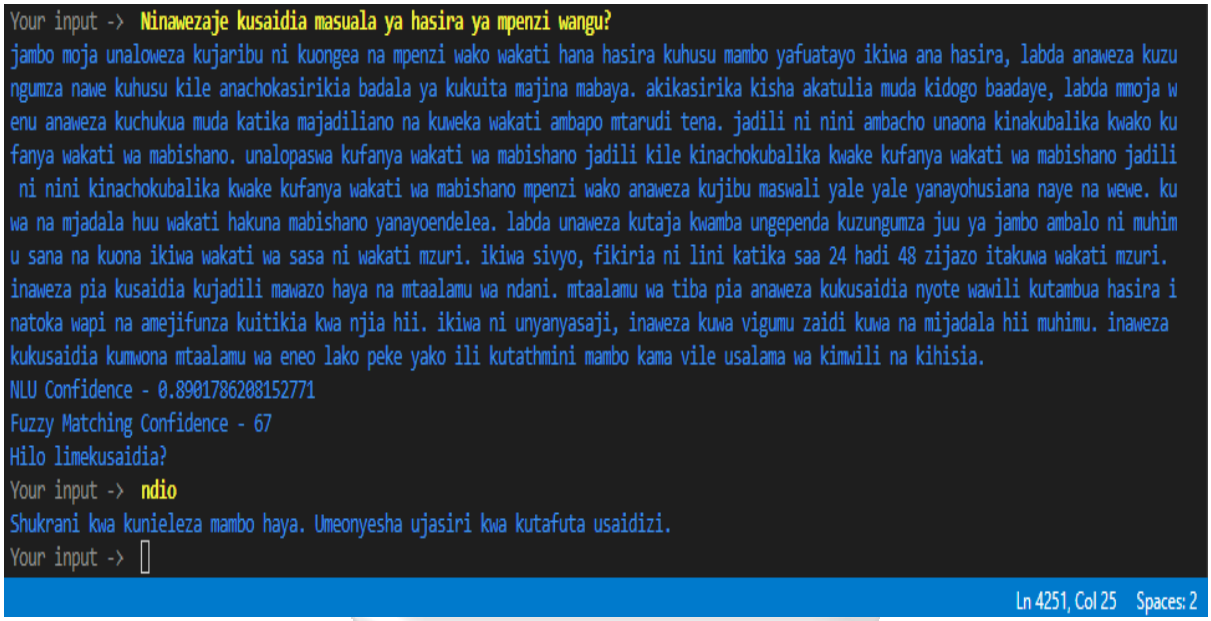


Figure 5.20: Conversation in Kiswahili with 89% NLU confidence and 67% Fuzzy Matching

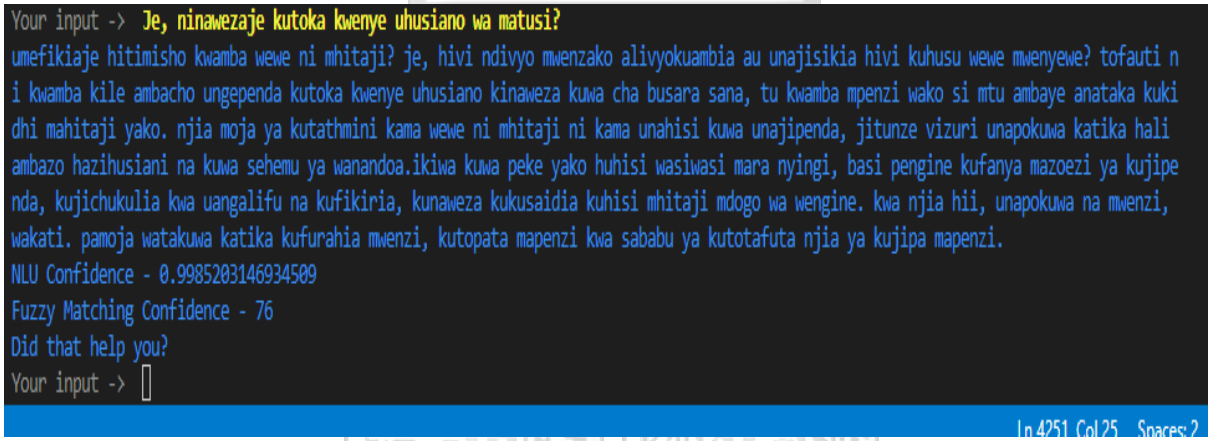


Figure 5.21: Conversation in Kiswahili with 99% NLU confidence and 76% Fuzzy Matching

As opposed to just picking any response randomly, the chatbot now provides the most suitable response based on the Fuzzy matching Token Set Ratio and displays the one with the highest matching score.

5.3.6 Deployment of the chatbot model

For the deployment of the Rasa chatbot model to the web application, the first step was to run both the Rasa server for the handling of the chatbot's dialogue management and Natural Language Understanding component and the custom actions server which handles the custom actions included in the chatbot's logic (Rasa Documentation, 2024). Running both servers is

required to be concurrent hence is conducted on two separate terminals where each must run. In the endpoints file in the Rasa project, there are 2 endpoints defined for this as shown below.

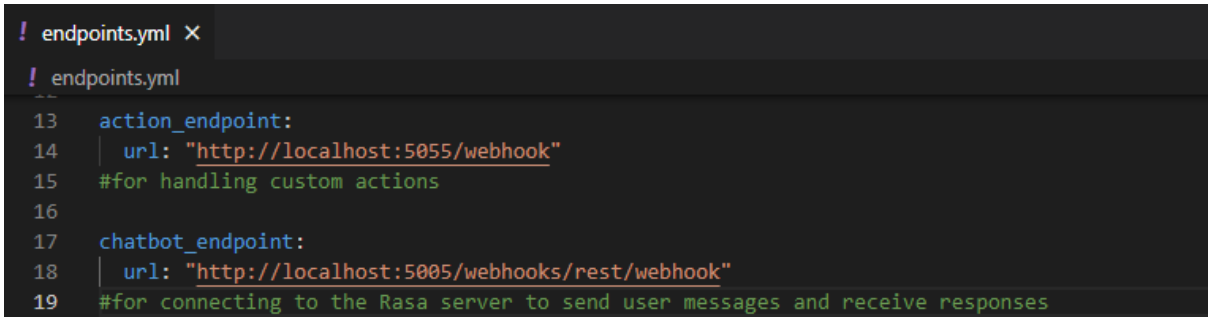


Figure 5.22: The Specified Endpoints

The commands utilized to start running the servers are:

rasa run --endpoints endpoints.yml --cors ""*

This command starts the Rasa server (REST Endpoint) with the specified endpoints configuration and allows Cross-Origin Resource Sharing (CORS) from all origins (--cors "*").

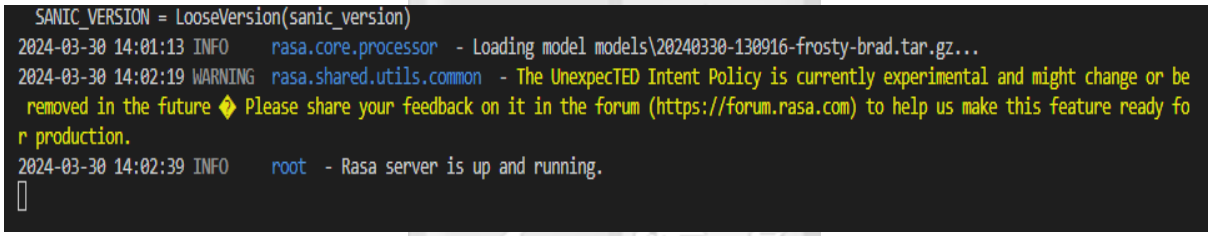


Figure 5.23: Rasa Server Feedback as Up and Running

rasa run actions

This command starts the custom actions server, which listens for requests from the Rasa server to execute custom actions.

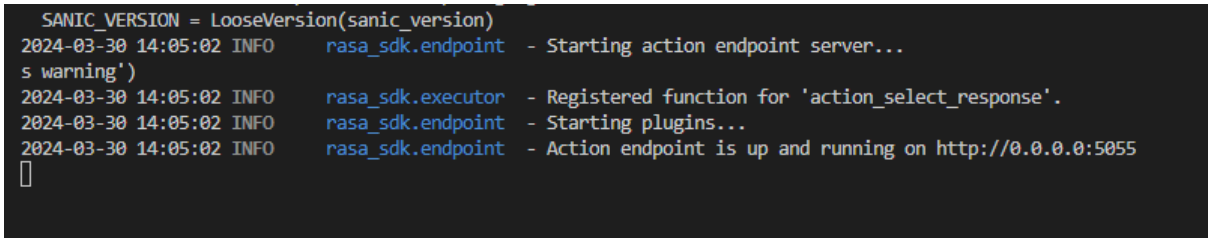


Figure 5.24: Rasa Actions Server Feedback as Up and Running

The web application was developed using html, css for the front end and Javascript for the back end. The Javascript Axios library was utilized to perform the HTTP requests which is the recommended method of handling versatile interactions and scenarios in Web applications and

preferred to the fetch API (Kholmatov, 2023; Bharali, 2023). The source code included the following JavaScript commands to ensure interactions with the chatbot model.

```
const chatBox = document.getElementById('chat-box');

const userInput = document.getElementById('user-input');
```

This command line is used for getting references to the chat box and user input elements contained in the HTML file.

```
function sendMessage() {
    // Get the message from the user input and trim whitespace
    const message = userInput.value.trim();
    // Check if the message is not empty
    if (message !== '') {
        // Append the user's message to the chat box
        appendMessage('User', message);
        // Clear the user input field
        userInput.value = '';
```

The '*sendMessage*` function is used for when the user sends a message and it performs the action of getting the message typed in by the user in the input field on the web application. The function appends this message to the chat interface as a user message after which it sends the message to the Rasa server using Axios JavaScript library.

```
        // Send a POST request to the Rasa server's REST API endpoint
        axios.post('http://localhost:5005/webhooks/rest/webhook', {
            message: message
        })
```

The Axios POST request was used to send the input message to the Rasa server endpoint `http://localhost:5005/webhooks/rest/webhook` and it expects a response back which is appemded to the chat interface as a bot message.

```
    .then(response => {
        // Get the chatbot's response from the response data
        const botResponse = response.data[0].text;
        // Append the chatbot's response to the chat box
        appendMessage('Bot', botResponse);
    })
```

The `appendMessage` function was then used for appending messages to the chat interface, which it does by creating a new `div` element for per message then appends it to the chat box in addition to scrolling the chat box to the bottom to show the latest message.

```
    .catch(error => {
        // Log any errors that occur
        console.error('Error:', error);
    });
// Function to append a message to the chat box
function appendMessage(sender, message) {
    // Create a new message element
    const messageElement = document.createElement('div');
    // Add a CSS class to the message element
    messageElement.classList.add('message');
    // Set the text content of the message element
    messageElement.textContent = `${sender}: ${message}`;
    // Append the message element to the chat box
    chatBox.appendChild(messageElement);
    // Scroll the chat box to the bottom to show the new message
    chatBox.scrollTop = chatBox.scrollHeight;
}
```

With all these set up, the interaction with the chatbot model through the defined endpoint using the chat interface on the web application was tested to confirm that it was functioning appropriately. This was successful, as illustrated below.

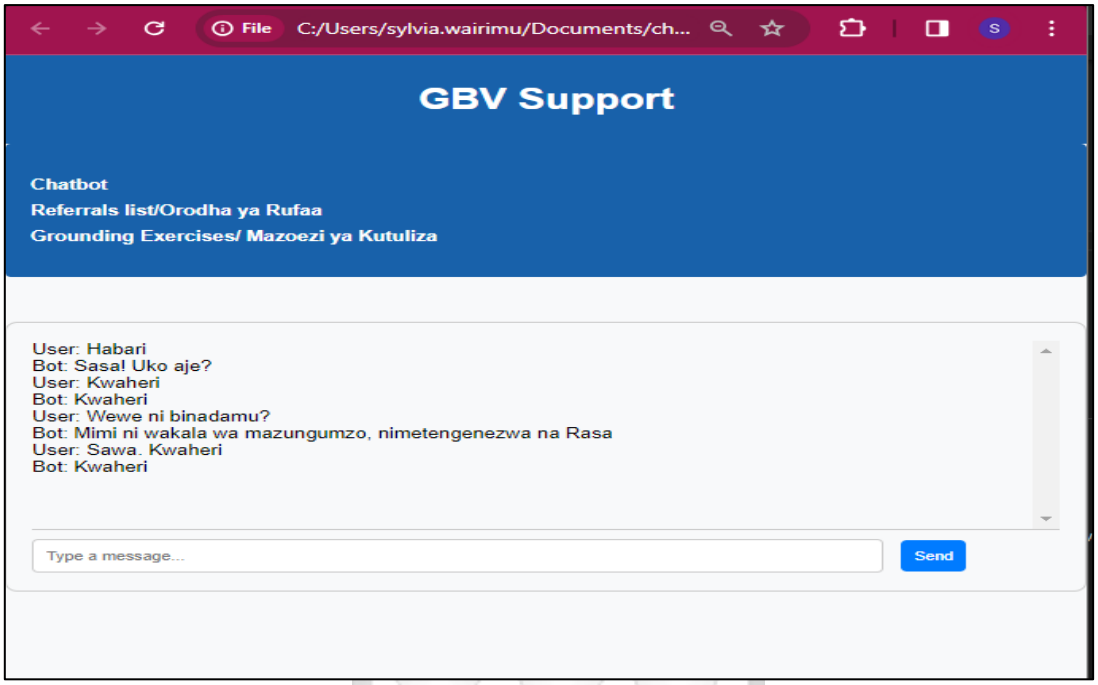


Figure 5.24: Interaction with the Chatbot Model on the Web Application

Deployment of the chatbot model on the Web application was, therefore, successful. Therefore, a user can access the web application through a URL on the browser then to interact with the chatbot model by providing an input on the chat interface provided on the web application then view the displayed response which is generated by the trained Rasa chatbot model.

VT OMNES VNVM SINT

Chapter 6: Discussions

6.1 Introduction

This chapter looks into findings from this research in addition to reviewing the results in comparison with the research objectives stated in Chapter 1 of the study. This study delved into establishing the challenges faced by Gender Based Violence victims in seeking for assistance in the amidst perceptions of stigma and bias influenced by cultural nuances and beliefs in addition to constraints in accessibility of resources when needed and affordability of the same. This research also examined technological interventions developed in the field of GBV for the uplifting of a victim's emotional wellbeing, specifically the use of conversational agents for counselling GBV victims due to their preference of using technological interventions compared to reaching out to human professionals to get assistance due to their experiences. Accordingly, after extensive investigation of the topic, the study determined to focus on development of a chatbot application by setting up and training a Rasa chatbot model that is capable of engaging a conversation with a victim in both English and Kiswahili and availing it via a web application, in addition to providing access to consolidated information on referral services available in Kenya for intervention and recommended grounding exercises a victim can utilize to de-escalate a situation of distress and being overwhelmed.

6.2 Discussion of Results

6.2.1 Accuracy of the Chatbot Application Response Generation

The development of the chatbot application included set up and training of a chatbot model using the Rasa Open-source Framework. A counselling dataset which includes queries from individuals to licensed therapists and responses provided by the counsellors that was obtained from a website which facilitates this platform was the data used to modify the NLU, Domain, Stories and Rules files in the created Rasa project for the chatbot application. The dataset was initially translated to Kiswahili and both the English and Swahili sets were combined so that a single bilingual model was created by subjecting the chatbot model to both languages. Using a Rasa interactive session, a conversation with the chatbot was held but the responses generated did not match the content of the query. This is because as much as the NLU component correctly identified the intent, the logic of the response generation was identified by randomly selecting the examples of responses listed in the intent's responses. Therefore, for enhancement of the chatbot's responses, different options were explored.

Rasa provides a custom actions component which enables inclusion of varied actions to be performed by a model such as querying databases, making API calls and adding events to a calendar and in this case, the custom actions was suitable to enable the enhancement of response generation using the Python FuzzyWuzzy library (Rasa Documentation, 2024). A python actions file was, therefore, created within the Rasa project which included the logic pf the custom action which used the FuzzyWuzzy library for better response generation. The algorithm within FuzzyWuzzy library called Token set ratio was determined to be the most accurate method for comparing the responses to the user's input and was preferred over the Fuzz Ratio, the Fuzz Partial Ratio and Token Sort Ratio (Pankajakshan & Sridevi, 2020). Token Set ratio was selected because of its consideration of the content's essence for the string as opposed to the specific order (Vitman, et al., 2022). Token Set Ratio was, therefore, implemented in the custom action source code for response generation. The FuzzyWuzzy enabled the picking of the best response out of the available responses by picking the one whose content best matched the query by the user because it scored higher than the rest of the responses as opposed to randomly selecting a response out of the listed ones in the intent's responses list from the counsellors' answers to the patients' queries.

Rasa Framework allows automated splitting of the dataset to create a test set for evaluation of the model performance in terms of NLU accuracy of intent classification by using a command "rasa data split nlu" (Rasa Documentation, 2024; White , 2020). This command withholds a test set from the training data utilized in training a model hence the test set is used at a later stage as a benchmark of evaluation of the model's generalization. Accordingly, in the development of the model, the split command was utilized, after which the "rasa train" command was implemented to train the model and further, the "rasa test nlu" to evaluate the model's NLU classification accuracy. A confusion matrix was generated by the testing command which is a grid which is a representation of the frequency that the model made a correct classification with the x-axis containing the model's predicted intent while the y-axis has the actual intent (Rasa Documentation, 2024; White , 2020). Correct classifications connect diagonally while others are the intents which the model mistook for others. When this was conducted on the developed model, the following confusion matrix was generated which illustrated that with the test data, the intent classification model was accurate every time because the matrix had a 100% accuracy.

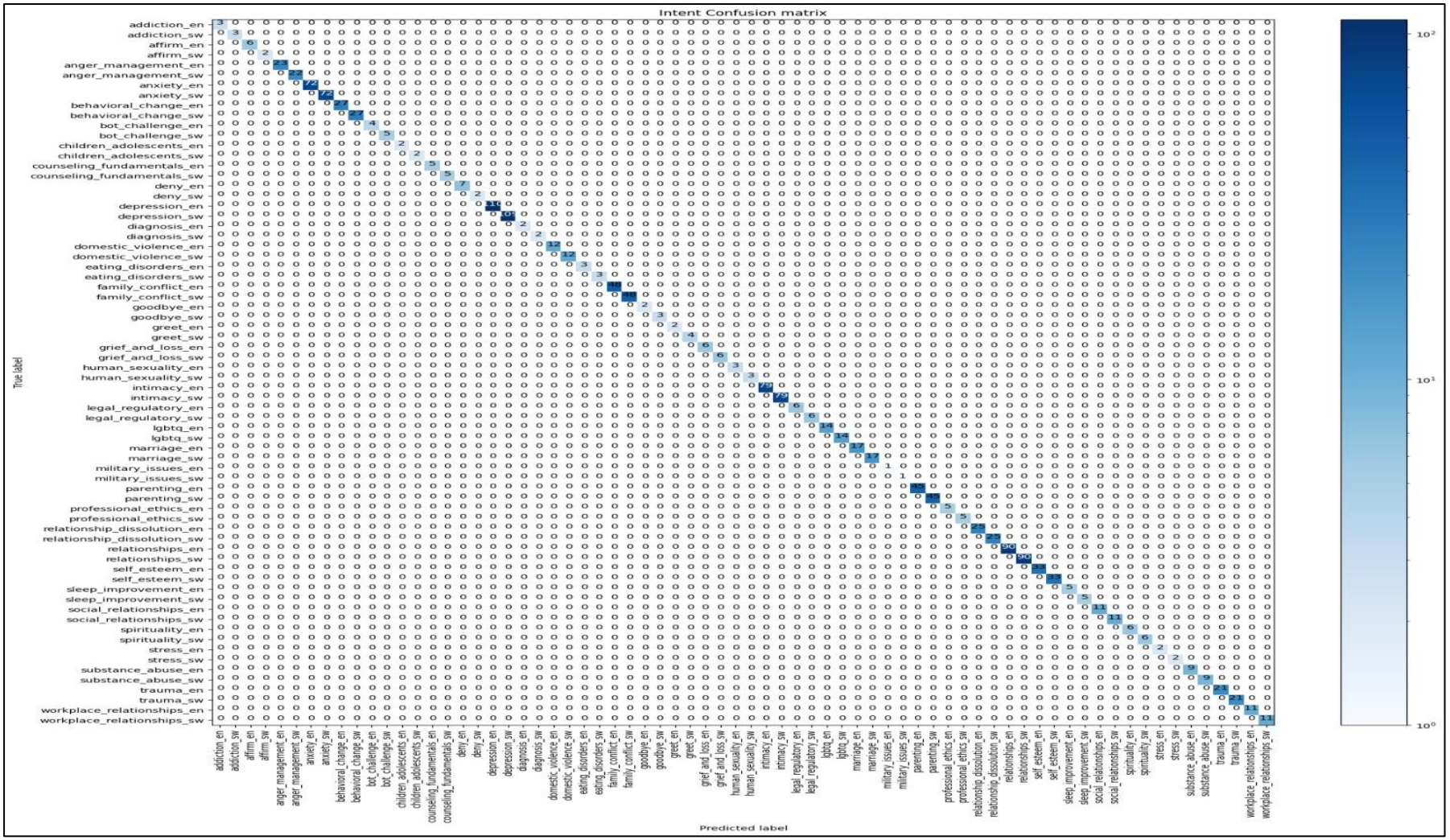


Figure 6.1: Generated NLU Classification Confusion Matrix

Consequently, further evaluation of the model was conducted through additional GBV queries with results as per figures 5.17, 5.18, 5.19 and 5.20 of this study. Figure 5.17 query in English indicated 76% NLU confidence and 92% Fuzzy Matching score which means that the NLU classification had 76% confidence that it had identified the correct intent from the input while the response generated had a Token Set Ratio of 92% which was the highest when the user input was compared with the responses listed for the identified intent. Further, figure 5.18 scored 82% NLU confidence and 63% Fuzzy Matching for an English GBV query meaning that the intent classification picked the intent with 82% which was the highest confidence level while the best matching response to the input out of the listed responses for the intent was the one generated and had a 63% Token set ratio score. Concurrently, a third query was made in Kiswahili as per figure 5.19 and it scored 89% NLU confidence and 67% Fuzzy Matching indicating that the intent selected with the highest confidence score had 89% while of this intent's responses, the best matching response in comparison with the input was generated and had a 67% Token set ratio. The fourth query as per figure 5.20 was in Kiswahili and scored 99% NLU confidence and 76% Fuzzy Matching. This means that the best fit intent which is the one that scored highest had a 99% certainty by the model that it picked the right intent while the best response out of the listed ones for this intent had a 76% Token Set Ratio. This indicated that the accuracy of the model in intent generalization for foreign queries was not as accurate but also scored between 76%-99% for the 4 queries made while the Token Set Ratio ranged between 63% and 92% for these same queries for both English and Kiswahili.

6.2.2 Attainment of Set Objectives

The study set to develop a bi-lingual chatbot application for counselling of GBV victims in Kenya using English and Kiswahili languages. Specifically, this research sought to first analyze the challenges experienced by GBV victims in Kenya, secondly, to analyze the weaknesses of the existing interventions to GBV, thirdly, to develop a chatbot for GBV counselling in English and Kiswahili and fourth, to validate the developed chatbot. The extensive challenges experienced by the victims of GBV were covered in Chapter 2 of this study including stigma, cultural beliefs, fear of consequences of seeking help, affordability and inadequate resources. Furthermore, to address the second objectives, related works were looked into to analyze their weaknesses and they were found to be insufficient for a GBV victim in Kenya due to language barrier and lack of referrals to resources available in Kenya. The next objective aimed at developing a bilingual chatbot capable of receiving input and generating responses in both English and Kiswahili. This was achieved by setting up and training a Rasa chatbot model

using a counselling dataset in English and Kiswahili by using specific columns of the dataset to come up with Rasa specific format for NLU, Stories, Rules and Domain files then including these training data files in the Rasa project to train the chatbot model. The fourth objective entailed validation of the developed model which was conducted by using Rasa Interactive sessions to query the chatbot model then check that the generated response was suitable in addition to displaying of the NLU confidence level that the correct intent was identified in addition to printing of the Fuzzy Matching Token Set Ratio Score to check the matching of the question string to the response generated by the model. The content of the question was compared to the content of the response in both English and Kiswahili to review the understanding of the NLU engine in addition to response selection to provide the best response. Therefore, to validate this chatbot application, a user needs to query the chatbot on an issue then review the displayed response on whether it is relevant and suitable to the question asked.

6.2.3 Advantages of the Developed Chatbot Application to the Related Applications

The developed Chatbot Application has the capability to converse in both English and Kiswahili which is significant for the target audience that encompasses GBV victims in Kenya where the dominant conversational languages are English and Kiswahili. This eliminates the language barrier challenge posed by related applications where the conversational agents use languages specific to their regions for effective dialogue. Having the Kiswahili option is key for a Kenyan audience because it ensures a more people can use the chatbot even if they do not have prowess in either of the 2 languages.

Additionally, the chatbot application has a web application as the user interface which also includes referral services in Kenya as opposed to related applications which refer users to referral services in their regions hence not being suitable for Kenyan GBV victims. Furthermore, the referral services provided in the web application interface contain information crucial to a victim's wellbeing because it provides names of organizations which offer intervention services such as the Hotlines for National GBV Rapid response, Gender Violence Recovery Centre contact information, Legal aid services and other information which a user can utilize to seek further assistance. This is, therefore, applicable to Kenyan GBV victims because they are within reach as compared to services in related applications which contain services available in their locations.

Consequently, the developed chatbot application is accessible by the use of a URL on any browser compared to some related applications which require installations because the user

interface is a mobile application. Additionally, to protect the user, the do not require to log in but can just access the web application and get the information needed and have a conversation with the chatbot without sharing their personal information. This is key for GBV victims because they face the fear of bias and stigma from seeking help so they often prefer to remain anonymous but still get the help they need. The web application can also be accessed through cyber cafes or borrowing devices then accessing the browser to get assistance hence being more inclusive even if one does not own a smart phone as is the requirement for related applications which must be installed. The developed chatbot application is, therefore, more suitable to assist the GBV victims in Kenya.

6.2.4 Shortfalls and Challenges of the study

Access to a GBV counselling dataset was a challenging exercise due to the sensitivity of the subject and policies surrounding sharing of mental health data. Studies discuss that there are strenuous processes and significant delays in access to quality mental health data characteristic of the data protection and privacy regulations which have to be carefully navigated and a tremendous caution taken because this is sensitive personal information which must remain anonymized and untraceable to an individual (Arseneault, 2022; Bertagnolli, 2020). After reaching out to some organizations to share anonymized GBV counselling dataset of any form including training material, therapy sessions and online psychotherapy packages, the organizations did not respond. The available datasets did not contain data that could be used to enhance response generation for a GBV counselling chatbot since most of the datasets contained statistics while the search was for a conversational dataset. After extensive search, the study arrived at a Data Science website which had been on a similar quest to get quality counselling data for use in improving mental health care using technology (Bertagnolli, 2020). The researchers contacted the founders of a counselling website who accepted to provide their anonymized dataset and have it availed publicly which included questions from patients and responses from licensed therapists (Bertagnolli, 2020). Therefore, for the training of this GBV chatbot application, this dataset was translated and pre-processed then converted to a suitable format for training. The challenge is that since it only contains 2128 rows representing this number of queries and responses, it is still limited due to the vast number of counselling topics hence the chatbot application model is limited to this response base. Inclusion of more data would further improve the responses generated by the chatbot due to a wider reference base (Brynjolfsson & McAfee, 2017).

The generation of responses by the current version of the Rasa Open-source framework is more static than dynamic. The developed chatbot application was created using Rasa 3.6.16 which only has capability to generate responses based on the available responses as defined in the domain file from the counselling dataset. Therefore, for enhancement of response selection from the initial random selection, Rasa custom actions had to be used to incorporate an external library, the python FuzzyWuzzy package, to facilitate matching of the responses to the query for the best of the available responses to be picked hence providing better suited responses. The study also tried to use Rasa Pro but it also did not have the capability for dynamic response generation where based on the available training data, a new response is generated which is customized to the query. According to Rasa Framework documentation, this capability of Contextual Response Rephrasing which ensures the generation of responses which are adaptable to the flow of the conversation and customizable will be available in Rasa 3.7 which is still in the testing phase and is available in the Rasa Pro Developer Edition where Rasa have introduced Conversational AI with Language Models (Harnett, 2024; Rasa Documentation, 2024).

VT OMNES VNVM SINT

Chapter 7 Conclusion and Recommendations

7.1 Conclusions

This study contributes to the resolution of the challenges faced by GBV victims in accessing assistance without being worried about the stigma, bias and burden they face when disclosing their experiences in addition to being an affordable tool accessible to all kinds of individuals in the country and having language options of English and Kiswahili. It enables the users to have access the help they need by simply clicking on a URL in a browser to access a conversational agent, referral services contact information and grounding exercises to de-escalate distress, all of which are aimed at improving the wellbeing of a GBV victim.

This research intended to perform an examination of the myriads of challenges that a GBV victim experiences in addition to delving into the weaknesses of the existing interventions to GBV so as to develop a better and more suited solution for victims of GBV in Kenya. This research then sought for a suitable counselling dataset and pre-processed it for use in developing a chatbot for GBV counselling in English and Kiswahili and availing the same on a web application. Refinement of the chatbot's responses based on the available responses from the dataset was implemented using custom actions by conducting Fuzzy Matching from the Python FuzzyWuzzy library and using the Token Set Ratio score to determine the best response from the listed responses in the identified intent. In the validation of the developed chatbot, GBV related queries were provided as input using the Rasa Interactive session which displayed the generated response in addition to the NLU confidence level of the identified intent and the Fuzzy Matching Token Set Ratio score to indicate the scoring of the best response or generate the Fallback response if the model did not understand the query.

The developed chatbot application performed satisfactorily well in responding to queries in both English and Kiswahili by its capability to switch languages during the conversation flow and based on the language input by the user. The chatbot application also performed satisfactorily in sending an input from the web application to the Rasa chatbot model and receiving the response from the model then displaying all via an endpoint without delays. The interaction from the web application chatbot-interface was seamless. The chatbot application includes more information on the web application which is essential to the wellbeing of the user because it contains referral services available in the country with contact information beneficial to the user in addition to recommended grounding exercises which the user can utilize to de-escalate a situation and stabilize themselves. However, the quality of the responses

generated was average as it was based on the available responses where the chatbot picks the best matching response hence the quality was limited to the dataset.

7.2 Recommendations

From the results discussed, the following are the recommendations from the researcher.

i. Once released, use of the Rasa Version 3.7 Contextual Response Rephraser is recommended to train the chatbot model to generate dynamic responses which are more natural and not limited to the available responses from the dataset but that can rephrase and customize the training data examples to improve the user interaction.

ii. Without limitations in time, the researcher recommends sourcing for additional datasets on GBV counselling to further build the chatbot's reference base for improved accuracy due to improvement in the model's capability to generalize.

iii. Continued updating of the training data is recommended to ensure the chatbot model is fed with the latest trends and data in addition to improvement of the chatbot application's performance.

VT OMNES VNVM SINT

References

Agrawal, A. (2019, December 4). *Agile Methodology: Incremental and Iterative Way of Development*. Retrieved from Medium.com: https://medium.com/@ashutoshagrawal1010/agile-methodology-incremental-and-iterative-way-of-development-a6614116ae68

AI for Good. (2018). *Our story*. Retrieved from AI for Good: https://www.aiforgood.co.uk/about-us

Al-Alosi, H. (2020). Fighting fire with fire: Exploring the potential of technology to help victims combat intimate partner violence. *Aggression and Violent Behavior*, Volume 52.

Aldkheel, A., & Zhou, L. (2023). How to Support Domestic Violence Survivors with Conversational Agents: Meta Requirements and Design Principles. *Pacific Asia Conference on Information Systems (PACIS) 2023* (pp. 1-18). Nanchang: Association for Information Systems (AISeL).

Allouch, M., Azaria, A., & Azoulay, R. (2021). Conversational Agents: Goals, Technologies, Vision and Challenges. *Sensors*, 8448 (1-48).

Alvin, C., Peterson, B., & Mukhopaghyay, S. (2021). Static generation of UML sequence diagrams. *International Journal of Software Tools for Technology Transfer*, 31-53.

Arseneault, L. (2022, January 7). *Infrastructures Fit for Purpose? The Complex Challenges in Sharing Mental Mealth Data*. Retrieved from The Mental Elf: https://www.nationalelfservice.net/commissioning/technology/sharing-mental-health-data/

Bertagnolli, N. (2020, May 11). *Counsel Chat: Bootstrapping High-Quality Therapy Data*. Retrieved from towardsdatascience.com: https://towardsdatascience.com/counsel-chat-bootstrapping-high-quality-therapy-data-971b419f33da

Bhandari, P. (2023, June 22). *Ethical Considerations in Research | Types & Examples*. Retrieved from Scribbr.com: https://www.scribbr.com/methodology/research-ethics/

Bharali, N. K. (2023). Full Stack Web Development of Redux-Based Web Applications with Dynamic Microservices (Case Study- Idea Repository). *International Research Journal of Modernization in Engineering Technology and Science*, DOI : https://www.doi.org/10.56726/IRJMETS33219.

Bore, S. K. (2019). Multilingual Education in Kenya: Implications for Culture Preservation and Transmission. *Bilingualism and Bilingual Education: Politics, Policies and Practices in a Globalized Society*, 125-146.

Bozhilov, Y. (2023, July 7). Differences between Conversational and Query-Response Approaches in Multimodal Interplay with a Robot. *University of Twente Student Theses*. Enschede, The Netherlands: Univerisity of Twente.

Brake, H. t., Willems, A., Steen, C., & Ducker, M. (2022). Appraising Evidence-Based Mental Health and Psychosocial Support (MHPSS) Guidelines—PART I: A Systematic Review on Methodological Quality Using AGREE-HS. *International Journal of Environmental Research and Public Health*, 3107(1-13).

Brynjolfsson, E., & McAfee, A. (2017). What's Driving the Machine Learning Explosion? *The Big Idea Series/ AI, For Real*.

Carroll, K., & Goodfriend, W. (2022, 02 16). *Validity & Reliability in Research*. Retrieved from Study.com: https://study.com/academy/lesson/validity-and-reliability-how-to-assess-the-quality-of-a-research-study.html

Chacha, L., & Iribemwangi, P. I. (2023). Challenges of Translating Conversational Implicatures from English to Kiswahili Using Computer Assisted Tools: A Case of Google Translate. *Mwanga wa Lugha*, 129-135.

Child Outcome Research Consortium. (2023). *The World Health Organisation- Five Well-Being Index (WHO-5)*. Retrieved from Mental Health Services : https://www.corc.uk.net/outcome-experience-measures/the-world-health-organisation-five-well-being-index-who-5/

Chowdhury, M. R., & Neuhaus, M. (2019, October 22). *What is Client Engagement in Therapy and How to Apply It?* Retrieved from Positive Psychology: https://positivepsychology.com/client-engagement/#:~:text=Successful%20treatment%20engagement%20includes%3A,communication%20between%20client%20and%20therapist.

Cobry Ltd. (2023, June 5). *How to best leverage the GCP Free Tier*. Retrieved from Cobry.co.uk: https://www.cobry.co.uk/gcp-free-tier

Despard, M. (2020, April 28). *DISSERTATION DATA: PRIMARY OR SECONDARY?* Retrieved from University of North Caroliba Greensboro (UNCG): https://hhs.uncg.edu/jpsw/dissertation-data-primary-or-secondary/

Dores, A. R., Geraldo, A., Carvalho, I. P., & Barbosa, F. (2020). The Use of New Digital Information and Communication Technologies in Psychological Counseling during the COVID-19 Pandemic. *International Journal of Environmentak Research and Public Health*, 7663.

Duckers, M., Hoof, W. V., Willems , A., & Brake, H. t. (2022). Appraising Evidence-Based Mental Health and Psychosocial Support (MHPSS) Guidelines—PART II: A Content Analysis with Implications for Disaster Risk Reduction. *International Journal of Environemtal Research and Public Health*, 7798(1-22).

Eisenhut, K., Sauerborn, E., Garcia-Moreno, C., & Wild, V. (2020). Mobile applications addressing violence against women: a systematic review . *BMJ global health*, e001954.

Fitzpatrick, K. K., Darcy, A., & Vierhile, M. (2017). Delivering Cognitive Behavior Therapy to Young Adults With Symptoms of Depression and Anxiety Using a Fully Automated Conversational Agent (Woebot): A Randomized Controlled Trial. *Journal of Medical Internet Research (JMIR) Mental Health*, Vol 4, No 2.

Fournier-Tombs, E., & McHardy, J. (2023). A Medical Ethics Framework for Conversational Artificial. *Journal of Medical Internet Research*, Vol. 25 e43068.

Government of Kenya. (2020). *Kenya National Action Plan for the Advancement of United Nations Security Council Resolution 1325.* Nairobi, Kenya: Ministry of Public Service and Gender, Ministry of Interior and Coordination of National Government, Kenya.

Griffing, E. (2023, July 23). *What is a Conversational Agent?* Retrieved from dashbot: https://www.dashbot.io/blog/conversational-agent#:~:text=A%20conversational%20agent%20is%20any,and%20virtual%20or%20AI%20assistants.

GVRC. (2023, June 30). *About Us*. Retrieved from Gender Violence Recovery Centre Kenya: https://gvrc.or.ke/about-us/

Harnett, K. (2024, February 29). *Elevate your Chatbot Conversations with the Contextual Response Rephraser*. Retrieved from RASA Tutorials : https://rasa.com/blog/elevate-your-chatbot-conversations-with-the-contextual-response-rephraser/

Harris, B., Dragiewicz, M., & Woodlock, D. (2020). Technology, Domestic Violence Advocacy and the Sustainable Development Goals. *The Emerald Handbook of Crime, Justice and Sustainable Development*, 295-313.

Hossain, E., Najib, A. U., & Islam, Z. (2020). Combating Domestic Violence during COVID-19 Pandemic in Bangladesh: Using a Mobile Application integrated with an Effective Solution. *23rd International Conference on Computer and Information Technology (ICCIT)* (pp. 1-6). DHAKA, Bangladesh: IEEE.

Inkster, B., Sarda, S., & Subramanian, V. (2018). An Empathy-Driven, Conversational Artificial Intelligence Agent (Wysa) for Digital Mental Well-Being: Real-World Data Evaluation Mixed-Methods Study. *JMIR Mhealth Uhealth*, 1-14.

Interaction Design Foundation. (2023, 08 12). *Design Iteration Brings Powerful Results. So, Do It Again Designer!* Retrieved from nteraction Design Foundation: https://www.interaction-design.org/literature/article/design-iteration-brings-powerful-results-so-do-it-again-designer

IRC. (2022, Nov 22). *What is gender-based violence – and how do we prevent it?* Retrieved from The IRC in the UK: https://www.rescue.org/uk/article/what-gender-based-violence-and-how-do-we-prevent-it

Khojah, R. (2022). Evaluating Confidence Estimation in NLU for Dialogue Systems. *Masters Thesis*. University of Gothenburg, Department of Philosophy, Linguistics and Theory of Science.

Kholmatov, A. (2023). Widely used Libraries in the JavaScript Programming Language and their Capabilities . *Intent Research Scientific Journal*, 18-25.

Khurana, D., Koli, A., Khatter, K., & Singh, S. (2022). Natural Language Processing: State of The Art, Current Trends and Challenges. *Multimedia Tools and Application*, 3713-3744.

KNBS and DHS Program. (2015). *Kenya Demographic and Health Survey 2014.* Nairobi, Kenya.

KNBS and ICF. (2023). *Kenya Demographic and Health Survey 2022, Key Indicators Report.* Nairobi, Kenya and Rockville, Maryland, USA: KNBS and ICF.

Kwamboka, D. (2022, December 6). *The road to ending violence against women and girls in Kenya*. Retrieved from World Vision Kenya: https://www.wvi.org/stories/kenya/road-ending-violence-against-women-and-girls-kenya#:~:text=In%20Kenya%2C%20just%20as%20in,partner%20violence%20in%20their%20lifetime.

Letaw, L. (2024). *Handbook of Software Engineering Methods (2nd Edition).* Corvallis, Oregon: Oregon State University.

Maeng, W., & Lee, J. (2021). Designing a Chatbot for Survivors of Sexual Violence: Exploratory Study for Hybrid Approach Combining Rule-based Chatbot and ML-based Chatbot. *Asian CHI Symposium*, (pp. 160-166).

Mental Health and Psychosocial Support Minimum Service Package. (2023, May 8). *3.11 Provide MHPSS as part of clinical care for survivors of sexual violence and intimate partner violence*. Retrieved from The Mental Health and Psychosocial Support Minimum Service Package: https://www.mhpssmsp.org/en/activity/relevant-guidelines-standards-and-tools-support-implementation-15#page-1

Middleton, F. (2023, June 22). *The 4 Types of Reliability in Research | Definitions & Examples*. Retrieved from Scribbr.com: https://www.scribbr.com/methodology/types-of-reliability/

Moret, J. D., Todd, A., Rose, L., Pollitt, E., & Anderson Jocelyn. (2022). Mobile Phone Apps for Intimate Partner and Sexual Violence Prevention and Response: Systematic Search on App Stores. *Journal of Medical Internet Research* , Vol 6, No 2.

Myrianthous, G. (2021, August 3). *Training vs Testing vs Validation Sets*. Retrieved from Towards Data Science: https://towardsdatascience.com/training-vs-testing-vs-validation-sets-a44bed52a0e1

Neetu, J., Charlotte, R., Mwangi, M., Neha, R., & McGovern, N. (2021). COVID-19 and gender-based violence (GBV): hard-to-reach women and girls, services, and programmes in Kenya. *Gender \& Development*, 55-71.

Okech, A. (2019). *Widow Inheritance and Contested Citizenship in Kenya.* Oxon: Routledge .

Pankajakshan, V., & Sridevi, M. (2020). Detecting Duplicate Question Pairs Using GloVe Embeddings and Similarity Measures. *International Conference on Automation, Signal Processing, Instrumentation an Control* (pp. 695-702). Singapore: Springer.

Park, H., & Lee, J. (2020). Can a Conversational Agent Lower Sexual Violence Victims' Burden of Self-Disclosure? *CHI: Conference on Human Factors in Computing Systems* (pp. 1-8). Honolulu HI USA: Association for Computing Machinery, New York, NY, United States.

Park, H., & Lee, J. (2021). Designing a Conversational Agent for Sexual Assault Survivors: Defining Burden of Self-Disclosure and Envisioning Survivor-Centered Solutions. *Association for Computing Machinery (ACM) Digital Library*, Article Number 634, Pages 1-17.

Park, H., & Lee, J. (2023). Can a Conversational Agent Lower Sexual Violence Victims' Burden of Self-Disclosure? *Association for Computing Machinery (ACM) Digital Library*, 1-8.

Patil, S., & Rasave, A. (2021). Artificial Intelligence Chat Bot for Counselling Therapy. *Proceedings of the 4th International Conference on Advances in Science & Technology (ICAST2021).* Mumbai: Elsevier BV.

Potts, C., Lindstrom, F., Bond, R., Mulvenna, M., Booth, F., Ennis, E., . . . O'Neill, S. (2023). A Multilingual Digital Mental Health and Well-Being Chatbot. *Journal of Medical Internet Research*, Vol. 25, e43051.

Rasa Documentation. (2024, March 27). *Contextual Response Rephraser*. Retrieved from Rasa Docs : https://rasa.com/docs/rasa-pro/concepts/contextual-response-rephraser/

Rasa Documentation. (2024, 3 21). *Rasa Open Source*. Retrieved from Rasa Documentation: https://rasa.com/docs/rasa/training-data-format

Rasa Documentation. (2024, March 21). *Testing Your Assistant*. Retrieved from Rasa Documentation: https://rasa.com/docs/rasa/testing-your-assistant/

Rasa Technologies . (2023, 11 10). *Your Own Website*. Retrieved from RASA Docs: https://rasa.com/docs/rasa/connectors/your-own-website/

Rasave, A., & Patil, S. R. (2021). Artificial Intelligence Chat Bot for Counselling Therapy. *Proceedings of the 4th International Conference on Advances in Science & Technology (ICAST2021)* (pp. 1-3). Mumbai: K J Somaiya Institute of Engineering and Information Technology.

Rathnayaka, P., Mills, N., Burnett, D., Silva, D. D., Alahakoon, D., & Gray, R. (2022). A Mental Health Chatbot with Cognitive Skills for Personalised Behavioural Activation and Remote Health Monitoring. *Sensors*, 22, 3653.

Ross-Hellauer, T., Tennant, J. P., Banelyte, V., Gorogh, E., Luzi, D., Kraker, P., . . . Vignoli, M. (2020). Ten simple rules for innovative dissemination of research. *PLoS Comput Biol*, e1007704.

Schobel, S., Schmitt, A., Benner, D., Saqr, M., Janson, A., & Leimeister, J. M. (2023). Charting the Evolution and Future of Conversational Agents: A Research Agenda Along Five Waves and New Frontiers. pp. 1-26.

Schyff, E. L., Ridout, B., Amon, K. L., Forsyth, R., & Campbell, A. J. (2023). Providing Self-Led Mental Health Support Through an Artificial Intelligence–Powered Chat Bot (Leora) to Meet the Demand of Mental Health Care. *Journal of Medical Internet Research*, Vol 25: e46448.

Shout It Now. (2021). *Our Technology and Innovation*. Retrieved from shoutitnow.org: https://shoutitnow.org/our-technology-and-innovation/

Spring ACT. (2022, Feb 26). *Who or What is "Sophia"?* Retrieved from Springact.org: https://springact.org/sophia-chatbot/

Terembe, C. (2022, May 31). *2022 List of Kenya-Based Therapists*. Retrieved from Terembe Cherono: https://www.terembecherono.com/personal/2022-list-of-kenya-based-therapists/

Tiun, S., Mokhtar, U. A., Bakar, S. H., & Saad, S. (2020). Classification of functional and non-functional requirement in software requirement using Word2vec and fast Text. *Journal of Physiscs Conference Series*, 042077.

Topp, C. W., Ostergaard, S. D., Sondergaard, S., & Bech, P. (2015). The WHO-5 Well-Being Index: a systematic review of the literature. *Psychother Psychosom*, 84(3):167-76. Retrieved from The WHO-5 Website.

Trappey, A. J., Lin, A. P., Hsu, K. Y., Trappey, C. V., & Tu, K. L. (2022). Development of an Empathy-Centric Counseling Chatbot System Capable of Sentimental Dialogue Analysis. *Processes* , 10, 930.

Tsili, E. P., & Katsamanis, A. (2023, March). A Voice Assistant for Cooking based on a Natural Language to SPARQL Transformation Pipeline using Rasa. *MSc Thesis*. Athens: National and Kapodistrian University of Athens.

UN. (2023). *Goal 5: Achieve gender equality and empower all women and girls*. Retrieved from UNRIC.ORG: https://unric.org/en/sdg-5/#top

UNFPA. (2020). *Guidelines for the Provision of Remote Psychosocial Support Services for GBV Survivors.* New York, United States: UNFPA. Retrieved from UNFPA.ORG.

UNFPA. (June 2022, June 23). *Turning pain to power: Women-led community-based organization leads economic empowerment and GBV protection in Kibera*. Retrieved from UNFPA Kenya: https://kenya.unfpa.org/en/news/turning-pain-power-women-led-community-based-organization-leads-economic-empowerment-and-gbv

UNFPA. (May 2022, May 10). *Soap-making and GBV prevention initiative expands to empower more women in Kibera*. Retrieved from UNFPA Kenya: https://kenya.unfpa.org/en/news/soap-making-and-gbv-prevention-initiative-expands-empower-more-women-kibera

UNHCR. (2017, Mar 15). *The Makonde: From Statelessness to Citizenship in Kenya*. Retrieved from UNHCR.org: https://www.unhcr.org/ke/10581-stateless-becoming-kenyan-citizens.html

Vainu, I. (2021, September 3). *Ultimate Guide for Creating Multilingual Chatbots*. Retrieved from alphachat: https://www.alphachat.ai/blog/multilingual-chatbot

Valderas, P., Torres, V., & Serral, E. (2023). Towards an Interdisciplinary Development of IoT-Enhanced Business Processes. *Business & Information Systems Engineering*, 25–48.

Vitman, O., Kostiuk, Y., Plachunda, P., Zhila, A., Sidorov, G., & Gelbukh, A. (2022). Evaluating the Impact of OCR Quality on Short Texts Classification Task. *Mexican International Conference on Artificial Intelligence MICAI 2022* (pp. 163-177). Cham: Springer.

Vivier, T. L. (2022, Oct 31). *Chomi: Chatbot Brings Tech to Fight Against Gender-Based Violence, Femicide*. Retrieved from goodthingsguy.com: https://www.goodthingsguy.com/opinion/chomi-chatbot-brings-tech-to-fight-against-gender-based-violence-femicide/

Wankhade, M., Rao, A. C., & Kulkarni, C. (2022). A Survey on Sentiment Analysis Methods, Applications, and Challenges. *Artificial Intelligence Review*, 5731-5780.

Wawire, G. N. (2017). *English-Swahili Code Switching: An Intersection between Stance and Indentity*. Electronic Theses and Dissertations.

White , K. (2020, April 27). *Write Tests! How to Make Automated Testing Part of Your Rasa Dev Workflow*. Retrieved from Rasa Technologies Inc: https://rasa.com/blog/rasa-automated-tests/

WHO. (2022). *Addressing violence against women in pre-service health training: Integrating content from the Caring for women subjected to violence curriculum.* Geneva: World Health Organization.

Wilson Center. (2023). *What is Gender-Based Violence (GBV)?* Retrieved from Wilson Center Organization Website: https://gbv.wilsoncenter.org/what-gender-based-violence

World Justice Project. (2021). *rAInbow: Chatbot to Support Victims of Domestic Abuse*. Retrieved from worldjusticeproject.org: https://worldjusticeproject.org/world-justice-challenge-2021/rainbow-chatbot-support-victims-domestic-abuse

Zachary, C., & Steinert, -T. (2018). *Twitter as Data.* Cambridge: Cambridge : Cambridge University Press.

Zhang, G., Bai, B., Liang, J., Bai, K., Zhu, C., & Zhao, T. (2020). Reliable Evaluations for Natural Language Inference based on a Unified Cross-dataset Benchmark. *Cornell University Computation and Language*.

Zhou, X., Nurkowski, D., Mosbach, S., Akroyd, J., & Kraft, M. (2021). Question Answering System for Chemistry. *Journal of Chemical Information and Modeling*, 3868-3880.

Appendices

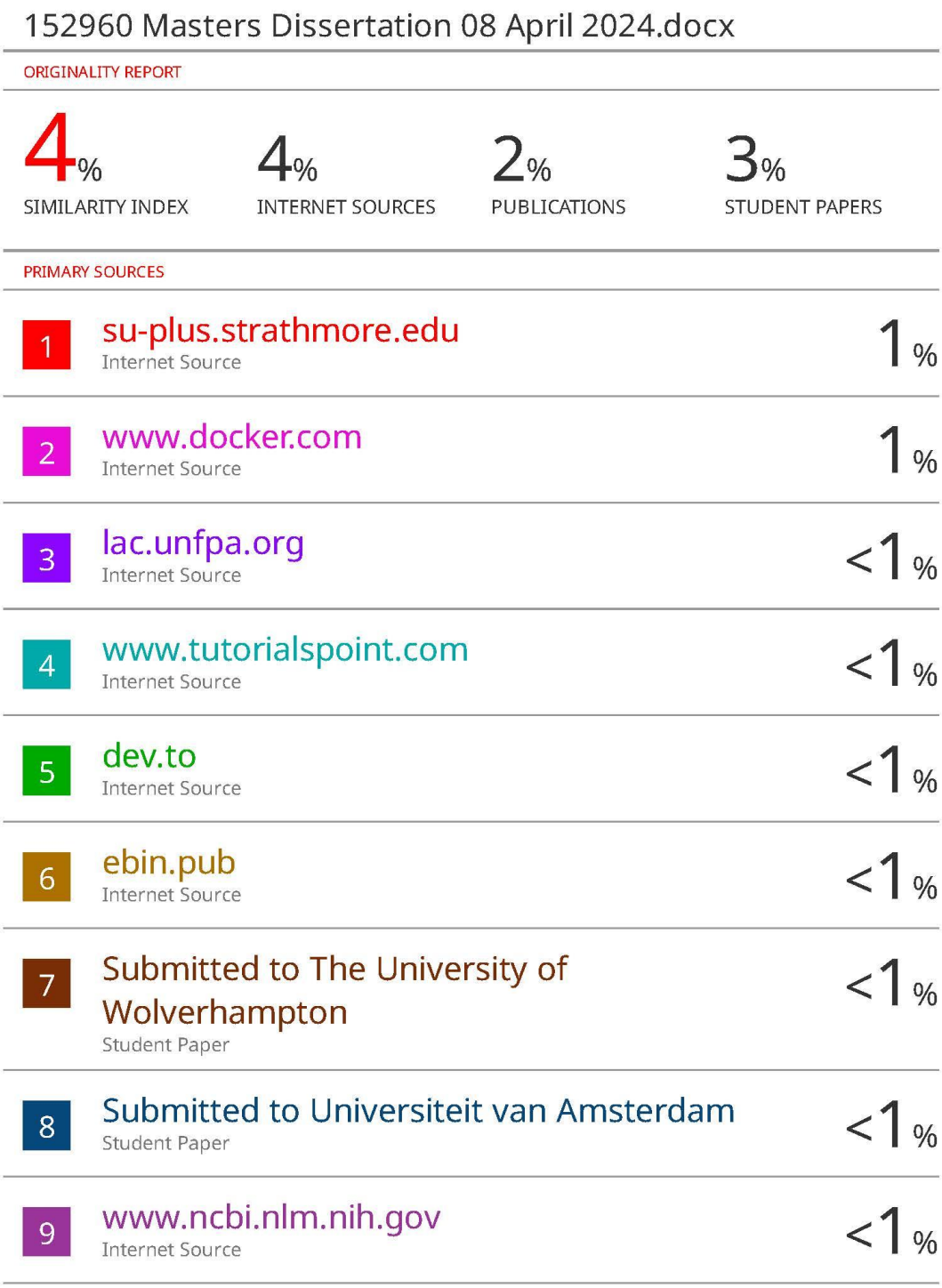
Appendix 1: The Chatbot Application Development Sprints

SPRINT NO.	ONE (1)	**DURATION**	2 WEEKS
TITLE	**Data Pre-processing and Multilingual Integration**		
OBJECTIVE	To prepare and pre-process the existing dataset and it into Kiswahili while maintaining data quality.		
FOCUS	1. Cleaning the data to address inconsistencies and errors.		
	2. Normalizing the dataset to ensure it has consistent data quality		
	3. Translating the dataset to Kiswahili.		
	4. Quality assurance check of the datasets to ensure they are accurate and appropriate		
SPRINT NO.	TWO (2)	**DURATION**	2 WEEKS
TITLE	**User input and Intent Recognition**		
OBJECTIVE	To develop the chatbot's ability to understand and recognize user input and intent		
FOCUS	1. Setting up the core of the chatbot's NLP/NLU capabilities		
	2. Integrate a natural language processing library into the chatbot framework.		
	3. Create and train an initial set of intent recognition models.		
	4. Implement basic dialogue flow for handling user queries.		
SPRINT NO.	THREE (3)	**DURATION**	4 WEEKS
TITLE	**Information Retrieval and Response Generation**		
OBJECTIVE	To enhance the chatbot's ability to retrieve information and generate meaningful responses to user queries.		
FOCUS/ TASKS	1. Integrate a knowledge base or data source that contains information relevant to GBV survivors.		
	2. Implement logic for information retrieval based on user queries.		

	3. Develop response generation mechanisms to provide helpful and empathetic responses. 4. Ensure that the chatbot provides appropriate responses		
SPRINT NO.	FOUR (4)	**DURATION**	2 WEEKS
TITLE	**Testing and Preparation for Deployment**		
OBJECTIVE	To perform comprehensive testing, fix any remaining issues, and prepare for deployment.		
FOCUS/ TASKS	1. Conduct end-to-end testing of the chatbot's functionalities.		
	2. Address any bugs, usability issues, or performance problems.		
	3. Prepare the chatbot for deployment to a web platform		
SPRINT NO	FIVE (5)	**DURATION**	2 WEEKS
TITLE	**User Interface development and chatbot deployment**		
OBJECTIVE	To create a user interface for the chatbot on a web application and deploy the chatbot on this web application		
FOCUS/ TASKS	1. Design a simple web application interface where users interact with the chatbot. 2. Deploy the chatbot on this web application		

VT OMNES VNVM SINT

Appendix 2: Similarity Report



152960 Masters Dissertation 08 April 2024.docx

ORIGINALITY REPORT

4%	4%	2%	3%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	su-plus.strathmore.edu Internet Source	1%
2	www.docker.com Internet Source	1%
3	lac.unfpa.org Internet Source	<1%
4	www.tutorialspoint.com Internet Source	<1%
5	dev.to Internet Source	<1%
6	ebin.pub Internet Source	<1%
7	Submitted to The University of Wolverhampton Student Paper	<1%
8	Submitted to Universiteit van Amsterdam Student Paper	<1%
9	www.ncbi.nlm.nih.gov Internet Source	<1%

10	www.rapecrisisscotland.org.uk Internet Source	<1%
11	erepository.uonbi.ac.ke:8080 Internet Source	<1%
12	Nassim Dehouche, Kullathida Dehouche. "What's in a text-to-image prompt? The potential of stable diffusion in visual arts education", Heliyon, 2023 Publication	<1%
13	repository.maseno.ac.ke Internet Source	<1%
14	Submitted to Colorado State University Student Paper	<1%
15	www.termpaperwarehouse.com Internet Source	<1%
16	Submitted to University of Northumbria at Newcastle Student Paper	<1%
17	Submitted to Campbellsville University Student Paper	<1%
18	swmath.org Internet Source	<1%
19	Submitted to City University of Seattle Student Paper	<1%
	hdl.handle.net	

20	Internet Source	<1%

Exclude quotes	On	Exclude matches	< 25 words
Exclude bibliography	On		

Appendix 3: Chatbot Application Source Code

0.1 Pre-processing for Domain

```
import pandas as pd


def preprocessing():
  data = pd.read_csv("dataset.csv", encoding = "unicode_escape") #Loading the
dataset


  data = data[["topic", "answer_text", "answer_text_translated"]] #Dropping
unnecessary columns


  print(data.isnull().values.any()) #Checking if there are any missing values

  data["topic"] = data["topic"].apply(lambda x: x.replace("-", "_"))
#replacing the - with _ for uniformity
  special_characters =['"', "", "\x98", "\x93", "\x94",  "\x9a", ":"]

  for column in data.columns:
    data[column] = data[column].apply(lambda x: x.lower()) #Converting to
lowercase
    data[column] = data[column].apply(lambda x: x.replace("\r", "\n"))
#Converting CR to LF
    for special_character in special_characters:
      data[column] = data[column].apply(lambda x: x.replace(special_character,
"")) #Removing special characters

  data.drop_duplicates(subset=["answer_text"], inplace=True) #dropping
duplicate english answers to avoid repeats



  data.to_csv("dataset_new_domain.csv", index = False) #Writing to csv (index
defaults to True therefore set to false)

  return data

print(preprocessing())
```

0.2 Pre-processing for NLU

```
import pandas as pd


def preprocessing():
  data = pd.read_csv("dataset.csv", encoding = "unicode_escape") #Loading the
dataset

  data = data[["question_title", "topic", "question_title_translated",
"topic_translated"]] #Dropping unnecessary columns

  data.isnull().values.any() #Checking if there are any missing values

  data["topic"] = data["topic"].apply(lambda x: x.replace("-", "_"))
#replacing the - with _ for uniformity
  data["topic_translated"] = data["topic_translated"].apply(lambda x:
x.replace("-", "_")) #replacing the - with _ for uniformity
  special_characters =['"', "", "\x98", "\x93", "\x94",  "\x9a", ":"]

  for column in data.columns:
    data[column] = data[column].apply(lambda x: x.lower()) #Converting to
lowercase
    data[column] = data[column].apply(lambda x: x.replace("\r", "\n"))
#Converting CR to LF
    for special_character in special_characters:
      data[column] = data[column].apply(lambda x: x.replace(special_character,
"")) #Removing special characters
  data.drop_duplicates(subset=["question_title"], inplace=True, keep="first")
#dropping duplicate questions to avoid repeating examples in nlu

  data.to_csv("dataset_new_nlu.csv", index = False) #Writing the training data
to csv (index defaults to True therefore set to False)

  return data

print(preprocessing())
```

0.3 Pre-processing for Rules

```
import pandas as pd

def preprocessing():
  data = pd.read_csv("dataset.csv", encoding = "unicode_escape") #Loading the
dataset


  data = data[["topic","topic_translated"]] #Dropping unnecessary columns


  print(data.isnull().values.any()) #Checking if there are any missing values

  data["topic"] = data["topic"].apply(lambda x: x.replace("-", "_"))
#replacing the - with _ for uniformity
  data["topic_translated"] = data["topic_translated"].apply(lambda x:
x.replace("-", "_")) #replacing the - with _ for uniformity
  special_characters =['"', "", "\x98", "\x93", "\x94",  "\x9a"]

  for column in data.columns:
    data[column] = data[column].apply(lambda x: x.lower()) #Converting to
lowercase
    data[column] = data[column].apply(lambda x: x.replace("\r", "\n"))
#Converting CR to LF
    for special_character in special_characters:
      data[column] = data[column].apply(lambda x: x.replace(special_character,
"")) #Removing special characters

  data.drop_duplicates(subset=["topic"], inplace=True) #dropping topics to
avoid repeats

  data = data[["topic", "topic_translated"]] #Extracting needed columns

  data.to_csv("dataset_new_rules.csv", index = False) #Writing to csv (index
defaults to True therefore set to false)

  return data

print(preprocessing())
```

0.4 Pre-processing for Stories

```
import pandas as pd


def preprocessing():
  data = pd.read_csv('dataset.csv', encoding = 'unicode_escape') #Loading the
dataset


  data = data[['topic','topic_translated']] #Dropping unnecessary columns


  print(data.isnull().values.any()) #Checking if there are any missing values

  data["topic"] = data["topic"].apply(lambda x: x.replace('-', '_'))
#replacing the - with _ for uniformity
  data["topic_translated"] = data["topic_translated"].apply(lambda x:
x.replace('-', '_')) #replacing the - with _ for uniformity
  special_characters =['"', "", "\x98", "\x93", "\x94",  "\x9a"]

  for column in data.columns:
    data[column] = data[column].apply(lambda x: x.lower()) #Converting to
lowercase
    data[column] = data[column].apply(lambda x: x.replace("\r", "\n"))
#Converting CR to LF
    for special_character in special_characters:
      data[column] = data[column].apply(lambda x: x.replace(special_character,
"")) #Removing special characters

  data.drop_duplicates(subset=['topic'], inplace=True) #dropping topics to
avoid repeats

  data.to_csv('dataset_new_stories.csv', index = False) #Writing to csv (index
defaults to True therefore set to false)

  return data

print(preprocessing())
```

0.5 Conversion for Domain

```
import pandas as pd

def conversion():
    df = pd.read_csv("dataset_new_domain.csv")  # Reading of the CSV file into
a DataFrame

    for column in df.columns:
        df[column] = df[column].apply(lambda x: x.replace("\n", " "))

    # Sorting the DataFrame by "topic" to group questions with the same topic
together
    # We are using topic as the intent in the NLU file and the domain file
    df.sort_values(by=["topic"], inplace=True)

    intents = {} # Initializing an empty dictionary to store examples for each
intent
    for index in df.index: # Iterating over each row in the DataFrame
        intent_name = df.loc[index, "topic"]   # Using "topic" as the intent
name
        answer_text=df.loc[index, "answer_text"] # the English response
        answer_text_translated=df.loc[index, "answer_text_translated"] # the
Swahili response

        if intent_name not in intents: # Checking if the intent already exists
in dictionary
            # Adding the intent to the dictionary if it doesn't exist
            intents[intent_name] = {
                "responses_en": [],
                "responses_sw": []
            }

        # Adding the English response for the current row to the intent's
responses list
        intents[intent_name]["responses_en"].append(answer_text)

        # Adding the Swahili response for the current row to the intent"s
responses list
        intents[intent_name]["responses_sw"].append(answer_text_translated)
    # Defining the domain template with the default intents
    domain_content = "intents: \n"
    domain_content += "  - greet_en\n"
    domain_content += "  - greet_sw\n"
    domain_content += "  - goodbye_en\n"
    domain_content += "  - goodbye_sw\n"
    domain_content += "  - affirm_en\n"
    domain_content += "  - affirm_sw\n"
    domain_content += "  - deny_en\n"
```

```
    domain_content += "  - deny_sw\n"
    domain_content += "  - bot_challenge_en\n"
    domain_content += "  - bot_challenge_sw\n"

    # Adding the remaining intents
    for intent_name in intents.keys():
        domain_content += f"  - {intent_name}_en\n"
        domain_content += f"  - {intent_name}_sw\n"

    # Adding the default responses
    domain_content += "\nresponses:\n"
    domain_content += "  utter_greet_en:\n"
    domain_content += "    - text: Hey! How are you?\n"
    domain_content += "      metadata:\n"
    domain_content += '        - language: "en"\n'
    domain_content += "  utter_greet_sw:\n"
    domain_content += "    - text: Sasa! Uko aje?\n"
    domain_content += "      metadata:\n"
    domain_content += '        - language: "sw"\n'

    domain_content += "  utter_introduction_en:\n"
    domain_content += "    - text: I am a bot powered by Rasa.\n"
    domain_content += "      metadata:\n"
    domain_content += '        - language: "en"\n'
    domain_content += "  utter_introduction_sw:\n"
    domain_content += "    - text: Mimi ni wakala wa mazungumzo.
Nimetengenezwa na Rasa.\n"
    domain_content += "      metadata:\n"
    domain_content += '        - language: "sw"\n'

    domain_content += "  utter_how_can_i_help_en:\n"
    domain_content += "    - text: How can I help?\n"
    domain_content += "      metadata:\n"
    domain_content += '        - language: "en"\n'
    domain_content += "  utter_how_can_i_help_sw:\n"
    domain_content += "    - text: Ungependa nikusaidie aje?\n"
    domain_content += "      metadata:\n"
    domain_content += '        - language: "sw"\n'

    domain_content += "  utter_did_that_help_en:\n"
    domain_content += "    - text: Did that help you?\n"
    domain_content += "      metadata:\n"
    domain_content += '        - language: "en"\n'
    domain_content += "  utter_did_that_help_sw:\n"
    domain_content += "    - text: Hilo limekusaidia?\n"
    domain_content += "      metadata:\n"
    domain_content += '        - language: "sw"\n'
```

```
    domain_content += "  utter_sign_off_en:\n"
    domain_content += "    - text: Thank you for sharing. It takes courage to
tell me your story.\n"
    domain_content += "      metadata:\n"
    domain_content += '        - language: "en"\n'
    domain_content += "  utter_sign_off_sw:\n"
    domain_content += "    - text: Shukrani kwa kunieleza mambo haya.
Umeonyesha ujasiri kwa kutafuta usaidizi.\n"
    domain_content += "      metadata:\n"
    domain_content += '        - language: "sw"\n'

    domain_content += "  utter_apologize_en:\n"
    domain_content += "    - text: I'm sorry to hear that. Please tell me more
about your situation.\n"
    domain_content += "      metadata:\n"
    domain_content += '        - language: "en"\n'
    domain_content += "  utter_apologize_sw:\n"
    domain_content += "    - text: Samahani kusikia hivyo. Tafadhali niambie
zaidi kuhusu hali yako.\n"
    domain_content += '      metadata: "sw"\n'

    domain_content += "  utter_goodbye_en:\n"
    domain_content += "    - text: Bye \n"
    domain_content += "      metadata:\n"
    domain_content += '        - language: "en"\n'
    domain_content += "  utter_goodbye_sw:\n"
    domain_content += "    - text: Kwaheri\n"
    domain_content += "      metadata:\n"
    domain_content += '        - language: "sw"\n'

    domain_content += "  utter_iamabot_en:\n"
    domain_content += "    - text: I am a bot, powered by Rasa. \n"
    domain_content += "      metadata:\n"
    domain_content += '        - language: "en"\n'
    domain_content += "  utter_iamabot_sw:\n"
    domain_content += "    - text: Mimi ni wakala wa mazungumzo,
nimetengenezwa na Rasa\n"
    domain_content += "      metadata:\n"
    domain_content += '        - language: "sw"\n'

    domain_content += "  utter_please_rephrase:\n"
    domain_content += "    - text: I'm sorry, I didn't quite understand that.
Could you rephrase?/Samahani, sijakuelewa. Tafadhali rudia. \n"

    for intent_name in intents.keys():
        #English
        domain_content += f"  utter_{intent_name}_en: \n"
        for response_en in intents[intent_name]["responses_en"]:
```

```
            domain_content += f"    - text: \"{response_en}\"\n".replace('"',
"")
        domain_content += "      metadata:\n"
        domain_content += '        - language: "en"\n'

        #Kiswahili
        domain_content += f"  utter_{intent_name}_sw: \n"
        for response_sw in intents[intent_name]["responses_sw"]:
            domain_content += f"    - text: \"{response_sw}\"\n".replace('"',
"")
        domain_content += "      metadata:\n"
        domain_content += '        - language: "sw"\n'

    #Actions
    domain_content += "\nactions:\n"
    domain_content += f" - action_select_response\n"

    #Session Config
    domain_content += "\nsession_config:\n"
    domain_content += f" session_expiration_time: 60 \n"
    domain_content += f" carry_over_slots_to_new_session: true \n"

    # Saving the yml string to a yml format file with "utf-8" encoding
    with open("domain_multilingual.yml", "w", encoding="utf-8") as file:
        file.write(domain_content)

print(conversion())
```

0.6 Conversion for NLU

```
import pandas as pd

def conversion():
    df = pd.read_csv("dataset_new_nlu.csv")  # Reading of the CSV file into a
DataFrame

    # Sorting the DataFrame by "topic" to group questions with the same topic
together
    #We are using topic as the intent in the NLU file
    df.sort_values(by=["topic"], inplace=True)

    intents = {} # Initializing an empty dictionary to store examples for each
intent

    for index in df.index: # Iterating over each row in the DataFrame
        intent_name = df.loc[index, "topic"] # Using "topic" as the intent
name
```

```
        question_title=df.loc[index, "question_title"] #the english question
title
        question_title_translated=df.loc[index, "question_title_translated"]
#the swahili question title

        if intent_name not in intents: # Checking if the intent already exists
in dictionary
                                    # Adding the intent to the dictionary if
it doesn"t exist
            intents[intent_name] = {
                "name": intent_name,  # the content of the "topic" column is
used as the intent
                "examples_en": [],
                "examples_sw": []
            }

            # Adding the example for the current row to the intent"s examples
list
        intents[intent_name]["examples_en"].append({
            "text": question_title,  #"questionTitle" is the English example
            "metadata": {
                "language": "en"
            }
        })
        intents[intent_name]["examples_sw"].append({
            "text": question_title_translated,  #"questionTitle_translated" is
the Swahili example
            "metadata": {
                "language": "sw"
            }
        })

    # Generating the nlu string
    nlu = "# Multilingual training data for Rasa NLU\n\n"
    nlu += "nlu:\n"

    #Defining the default intents
    nlu += "- intent: greet_en\n"
    nlu += "  examples: |\n"
    nlu += "    - hello\n"
    nlu += "    - hi\n"
    nlu += "  metadata:\n"
    nlu += '    - language: "en"\n'
    nlu += "- intent: greet_sw\n"
    nlu += "  examples: |\n"
    nlu += "    - habari\n"
    nlu += "    - hujambo\n"
    nlu += "    - sasa\n"
```

```
    nlu += "    - habari ya leo\n"
    nlu += "  metadata:\n"
    nlu += '    - language: "sw"\n'

    nlu += "- intent: goodbye_en\n"
    nlu += "  examples: |\n"
    nlu += "    - goodbye\n"
    nlu += "    - bye\n"
    nlu += "  metadata:\n"
    nlu += '    - language: "en"\n'
    nlu += "- intent: goodbye_sw\n"
    nlu += "  examples: |\n"
    nlu += "    - kwaheri\n"
    nlu += "    - tutaonana baadaye\n"
    nlu += "    - tuonane\n"
    nlu += "  metadata:\n"
    nlu += '    - language: "sw"\n'

    nlu += "- intent: affirm_en\n"
    nlu += "  examples: |\n"
    nlu += "      - yes\n"
    nlu += "      - y\n"
    nlu += "      - indeed\n"
    nlu += "      - of course\n"
    nlu += "      - that sounds good\n"
    nlu += "      - correct\n"
    nlu += "  metadata:\n"
    nlu += '    - language: "en"\n'
    nlu += "- intent: affirm_sw\n"
    nlu += "  examples: |\n"
    nlu += "      - sawa\n"
    nlu += "      - ndio\n"
    nlu += "  metadata:\n"
    nlu += '    - language: "sw"\n'

    nlu += "- intent: deny_en\n"
    nlu += "  examples: |\n"
    nlu += "    - no\n"
    nlu += "    - n\n"
    nlu += "    - never\n"
    nlu += "    - I don't think so\n"
    nlu += "    - don't like that\n"
    nlu += "    - no way\n"
    nlu += "    - not really\n"
    nlu += "  metadata:\n"
    nlu += '    - language: "en"\n'
    nlu += "- intent: deny_sw\n"
    nlu += "  examples: |\n"
```

```
    nlu += "    - la\n"
    nlu += "    - hapana\n"
    nlu += "  metadata:\n"
    nlu += '    - language: "sw"\n'

    nlu += "- intent: bot_challenge_en\n"
    nlu += "  examples: |\n"
    nlu += "    - are you a bot?\n"
    nlu += "    - are you human?\n"
    nlu += "    - am I talking to a bot?\n"
    nlu += "    - am I talking to a human?\n"
    nlu += "  metadata:\n"
    nlu += '    - language: "en"\n'
    nlu += "- intent: bot_challenge_sw\n"
    nlu += "  examples: |\n"
    nlu += "    - wewe ni binadamu?\n"
    nlu += "    - wewe ni mtu?\n"
    nlu += "    - ninazungumza na wakala?\n"
    nlu += "    - naongea na mtu?\n"
    nlu += "    - wewe ni nani au nini?\n"
    nlu += "  metadata:\n"
    nlu += '    - language: "sw"\n'

    # Defining the remaining intents
    for intent_data in intents.values():
        #English
        nlu += f"- intent: {intent_data['name']}_en\n"
        nlu += "  examples: |\n"
        for example_en in intent_data["examples_en"]:
            nlu += (f"    - \"{example_en['text']}\"\n").replace('"', "")
        nlu += "  metadata:\n"
        nlu += '    - language: "en"\n'

        #Kiswahili
        nlu += f"- intent: {intent_data['name']}_sw\n"
        nlu += "  examples: |\n"
        for example_sw in intent_data["examples_sw"]:
            nlu += (f"    - \"{example_sw['text']}\"\n").replace('"', "")
        nlu += "  metadata:\n"
        nlu += '    - language: "sw"\n'
    # Saving the nlu string to a YAML format file with "utf-8" encoding
    with open("nlu_multilingual.yml", "w", encoding="utf-8") as file:
        file.write(nlu)
print(conversion())
```

0.7 Conversion for Rules

```
import pandas as pd

def conversion():
  df = pd.read_csv('dataset_new_rules.csv')  # Reading of the CSV file into a
DataFrame
  rules = "rules: \n \n"
  rules += "- rule: Saying goodbye en\n" # Adding default rules
  rules += "  steps: \n"
  rules += "    - intent: goodbye_en \n"
  rules += "    - action: utter_goodbye_en\n"
  rules += "- rule: Saying goodbye sw\n"
  rules += "  steps: \n"
  rules += "    - intent: goodbye_sw \n"
  rules += "    - action: utter_goodbye_sw\n"

  rules += "- rule: Responding to questions about being a bot en\n"
  rules += "  steps: \n"
  rules += "    - intent: bot_challenge_en \n"
  rules += "    - action: utter_iamabot_en\n"
  rules += "- rule:  Responding to questions about being a bot sw\n"
  rules += "  steps: \n"
  rules += "    - intent: bot_challenge_sw \n"
  rules += "    - action: utter_iamabot_sw\n"

  rules += "- rule: Ask the user to rephrase whenever they send a message with
low NLU confidence\n" #Adding the fallback
  rules += "  steps: \n"
  rules += "    - intent: nlu_fallback \n"
  rules += "    - action: utter_please_rephrase \n"

  # Saving the rules string to yaml format file with 'utf-8' encoding
  with open("rules.yml", "w", encoding="utf-8") as file:
    file.write(rules)

  return rules

print(conversion())
```

0.8 Conversion for Stories

```
import pandas as pd

def conversion():
    df = pd.read_csv('dataset_new_stories.csv')  # Reading of the CSV file
into a DataFrame
```

```
    stories = "stories:\n" # Initializing an empty string store to store
examples for each intent

    stories += "- story: intro_en\n"
    stories += "  steps:\n"
    stories += "    - intent: greet_en\n"
    stories += "    - action: utter_greet_en\n"
    stories += "    - action: utter_introduction_en\n"
    stories += "    - action: utter_how_can_i_help_en\n"
    stories += "    - checkpoint: ask_user_for_query_en\n"

    stories += "- story: intro_sw\n"
    stories += "  steps:\n"
    stories += "    - intent: greet_sw\n"
    stories += "    - action: utter_greet_sw\n"
    stories += "    - action: utter_introduction_sw\n"
    stories += "    - action: utter_how_can_i_help_sw\n"
    stories += "    - checkpoint: ask_user_for_query_sw\n"

    stories += "- story: outro_affirm_en\n"
    stories += "  steps:\n"
    stories += "    - checkpoint: ask_user_for_query_en\n"
    stories += "    - intent: affirm_en\n"
    stories += "    - action: utter_sign_off_en\n"

    stories += "- story: outro_affirm_sw\n"
    stories += "  steps:\n"
    stories += "    - checkpoint: ask_user_for_query_sw\n"
    stories += "    - intent: affirm_sw\n"
    stories += "    - action: utter_sign_off_sw\n"

    stories += "- story: outro_deny_en\n"
    stories += "  steps:\n"
    stories += "    - checkpoint: check_if_user_is_satisfied_en\n"
    stories += "    - intent: deny_en\n"
    stories += "    - action: utter_apologize_en\n"
    stories += "    - checkpoint: ask_user_for_query_en\n"

    stories += "- story: outro_deny_sw\n"
    stories += "  steps:\n"
    stories += "    - checkpoint: check_if_user_is_satisfied_sw\n"
    stories += "    - intent: deny_sw\n"
    stories += "    - action: utter_apologize_sw\n"
    stories += "    - checkpoint: ask_user_for_query_sw\n"

    for topic in df["topic"]:
        #English
        stories += f"- story: ask about {topic}_en\n"
```

```
        stories += f"  steps:\n"
        stories += f"    - checkpoint: ask_user_for_query_en\n"
        stories += f"    - intent: {topic}_en\n"
        stories += f"    - action: action_select_response\n"
        stories += f"    - action: utter_did_that_help_en\n"
        stories += f"    - checkpoint: check_if_user_is_satisfied_en\n"

        #Kiswahili
        stories += f"- story: ask about {topic}_sw\n"
        stories += f"  steps:\n"
        stories += f"    - checkpoint: ask_user_for_query_sw\n"
        stories += f"    - intent: {topic}_sw\n"
        stories += f"    - action: action_select_response\n"
        stories += f"    - action: utter_did_that_help_sw\n"
        stories += f"    - checkpoint: check_if_user_is_satisfied_sw\n"

    # Saving the stories string to yaml format file with 'utf-8' encoding
    with open('stories.yml', 'w', encoding='utf-8') as file:
        file.write(stories)

    return stories

print(conversion())
```

0.9 Custom Action for Fuzzy Matching and NLU Confidence Scores

```
from fuzzywuzzy import fuzz
from typing import Any, Text, Dict, List
from rasa_sdk import Action, Tracker
from rasa_sdk.executor import CollectingDispatcher


class ActionSelectResponse(Action):
  def name(self) -> Text:
    return "action_select_response"

  def run(self, dispatcher: CollectingDispatcher, tracker: Tracker, domain:
Dict[Text, Any]) -> List[Dict[Text, Any]]:
    #Defining the user's most recent input
    current_input = tracker.latest_message['text']
    #Identifying the intent and confidence
    current_intent = tracker.latest_message['intent']['name']
    confidence = tracker.latest_message['intent']['confidence']
    #Extracting the responses for the identified intent
    responses = []
    for response in domain['responses'][f'utter_{current_intent}']:
      responses.append(response['text'])
    #Finding the most appropriate response based on the current_statement
    scores = []
    for response in responses:
      scores.append(fuzz.token_set_ratio(response, current_input))
    #Responding to the user
    dispatcher.utter_message(text = responses[scores.index(max(scores))])
    dispatcher.utter_message(text = f'NLU Confidence - {confidence}')
    dispatcher.utter_message(text = f'Fuzzy Matching Confidence -
{max(scores)}')
    return []
```

0.10 Endpoints File

```
action_endpoint:
  url: "http://localhost:5055/webhook"
#for handling custom actions

chatbot_endpoint:
  url: "http://localhost:5005/webhooks/rest/webhook"
```

0.11 Configuration File

```yaml
# The config recipe.
# https://rasa.com/docs/rasa/model-configuration/
recipe: default.v1

# The assistant project unique identifier
# This default value must be replaced with a unique assistant name within your
deployment
assistant_id: gbv_bot

# Configuration for Rasa NLU.
# https://rasa.com/docs/rasa/nlu/components/
language: multilingual

pipeline:
# # No configuration for the NLU pipeline was provided. The following default
pipeline was used to train your model.
# # If you'd like to customize it, uncomment and adjust the pipeline.
# # See https://rasa.com/docs/rasa/tuning-your-model for more information.
   - name: WhitespaceTokenizer
   - name: RegexFeaturizer
   - name: LexicalSyntacticFeaturizer
   - name: CountVectorsFeaturizer
   - name: CountVectorsFeaturizer
     analyzer: char_wb
     min_ngram: 1
     max_ngram: 4
   - name: DIETClassifier
     epochs: 100
     constrain_similarities: true
   - name: EntitySynonymMapper
   - name: ResponseSelector
     epochs: 100
     constrain_similarities: true
   - name: FallbackClassifier
     threshold: 0.5
     ambiguity_threshold: 0.1
```

Appendix 4: Ethical Approval Letter

22nd November 2023

Ms Mutinda Sylvia Wairimu,
sylvia.wairimu@strathmore.edu

Dear Ms Mutinda,

RE: A Bi-Lingual Counselling Chatbot Application for Support of Gender Based Violence Victims in Kenya

This is to inform you that SU-ISERC has reviewed and **approved** your above **SU-masters** research proposal. Your application reference number is **SU-ISERC1921/23.** The approval period is from **22nd November 2023 to 21st November 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 72 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 72 hours.
v. Clearance for the 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 the expiry of the approval period. Attach a comprehensive progress report to support the renewal.
vii. Submission of an executive summary report within 90 days of completion of the study to SU-ISERC.

Before 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,

Mr Ambrose Rachier,
Chairperson; SU-ISERC

STRATHMORE UNIVERSITY INSTITUTIONAL SCIENTIFIC AND ETHICAL REVIEW COMMITTEE
(SU-ISERC)
22-Nov-2023
Email:ethicsreview@strathmore.edu
P.O BOX 59857-00200
NAIROBI-KENYA