University of Ibadan
Journal of Science and Logics in ICT Research

A Web Based Chatbot for Mental Health Support

[1]✉Samuel, E. L. and [2]Akinola, S. O.
Nigeria University of Technology
luckysamuel49@gmail.com
University of Ibadan, Nigeria
akinola.olalekan@dlc.ui.edu.ng

Abstract

This study explores the development of a web-based chatbot designed to provide personalized mental health therapy, addressing the challenge of accessing timely mental health interventions. The chatbot, developed using a dataset of mental health-related FAQs, employs lemmatization, lowercasing, and duplication removal to prepare data for analysis. Utilizing neural networks, particularly LSTM architecture, the machine learning model shows a negative correlation between training epochs and loss magnitude, indicating improved performance over time. The findings reveal the chatbot's high proficiency in delivering individualized care, quick response, and relevant therapy recommendations. The study underscores the efficacy of chatbots in mental health care, enhancing resource availability and addressing societal stigma, limited resources, and geographical isolation issues. It recommends continuous updates to the chatbot's knowledge base, therapy suggestions, and conversational skills, ensuring its relevance and effectiveness in providing personalized mental health care. This highlights the potential of advanced chatbots in revolutionizing mental health interventions and support

Keywords: Lemmatization, LSTM architecture, Machine learning model, Mental health, Personalized therapy

1. Introduction

According to Health [1], a sizeable percentage of the world's population or around 900 million people, have battled a wide range of mental health illnesses at some point in their lives. These conditions include, but are not limited to, anxiety, depression, psychosis, and personality disorders. People who struggle with mental illness typically experience a significant drop in their level of living, in addition to a decrease in their contribution to society and the economy. The estimated annual cost to the global economy caused by the cumulative negative impact is USD 2.5 trillion, and it is anticipated that this number would rise to USD 6 trillion by the year 2030 [2].

Through the implementation of its Special Initiative for Mental Health (2019-2023), the World Health Organization (WHO) has brought attention to the critical need for mental healthcare and treatment. According to the World Health Organization (2019), the purpose of this program is to increase the number of individuals in 12 high-priority countries who have access to treatment that is both of high quality and within their financial means for mental health illnesses. When it comes to the treatment of mental diseases, a wide variety of therapies, both pharmacological and non-pharmacological, are typically prescribed [2]. Some examples of these interventions are surgical procedures, in-patient and out-patient care, medication, support groups, counseling, psycho-social interventions, behavioral therapy, and alternative therapies. The categorization of the condition and the severity level both have a role in the decision-making process on the intervention that should be utilized. Formal taxonomies for the classification of mental illnesses include the International Classification of Diseases (ICD), which was produced by the World Health Organization (WHO), and the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), which was produced by the American Psychiatric Association (APA). In order to accomplish this

Samuel, E. L. and Akinola, S. O. (2024). A Web Based Chatbot for Mental Health Support. *University of Ibadan Journal of Science and Logics in ICT Research (UIJSLICTR),* Vol. 10 No. 2, pp. 152 -. 163

goal, these systems make use of standardized criteria and a shared language [2] [3].

The Diagnostic and Statistical Manual of Mental diseases, Fifth Edition (DSM-5) and the International Classification of Diseases (ICD) each recognize 11 and 20 primary classifications of psychiatric diseases, respectively. Anxiety and depression are the most common forms of mental illness, particularly among people of working age, according to a study that was conducted by Regier *et. al.* [4]. According to research carried out by Oud *et. al.* [5], the use of psychosocial and behavioral therapies is commonly recognized as the preferable non-pharmacological technique for controlling anxiety and depression.

The application of artificial intelligence (AI) in the medical field has resulted in a substantial paradigm shift. It has altered the methods of diagnosis, treatment, and monitoring, which has resulted in a revolutionary shift in the approach to patient care. Through the supply of accurate diagnoses and the facilitation of individualized treatment options, the application of this technology has substantially improved both the research conducted in the healthcare industry and the results obtained. It is possible that medical professionals would not have been able to recognize certain illness markers and patterns if it were not for the ability of artificial intelligence (AI) in the healthcare industry to rapidly examine large amounts of clinical documentation [6]. This ability enables the identification of disease markers and patterns.

Within the realm of natural user interface design, conversational artificial intelligence (AI) has garnered a significant amount of interest. Because of its rapid expansion, the area of machine learning has attracted major attention from three distinct research groups. These communities are natural language processing (NLP), information retrieval (IR), and machine learning (ML). In spite of this, the application of deep learning (DL) and reinforcement learning (RL) methodologies in the context of conversational artificial intelligence (AI) is widely recognized as a remarkable accomplishment, as Fuad, and Al-Yahya [7] point out. This is the case despite the fact that deep learning (DL) and RL are both types of machine learning. As a direct result of this, academics have shifted their attention to improving end-to-end models of artificial intelligence (AI) systems that are used in conversation.

Chatbots, in contrast to computer-aided tools, which require human skill, function totally online and in an automated manner. This enables them to be effective in providing primary support for mental health illnesses. Chatbots make use of natural language processing, and they have attracted a lot of attention due to the fact that they are able to provide a wide variety of services through a single point of interaction. Chatbots have been adopted in a variety of fields, including education, banking, customer service, and healthcare, in order to improve the quality of services provided and the overall experience provided to customers. Recently,

There has been a boom in the creation of digital interventions in the field of mental health [8] [9]. These digital interventions can be used as a complementary or alternative method to traditional face-to-face mental health services. According to the body of literature that is currently available, the utilization of chatbots results in a wide range of benefits. It has been seen that certain people have a preference for utilizing chatbots for the execution of specific tasks that are traditionally carried out on web sites or mobile applications. This preference can be attributed to the fact that chatbots provide a more natural user experience.

Despite the importance of mental health, many people still have trouble getting the timely and individualized mental health treatment they need, which may be caused by social stigma, lack of available resources, or a remote location Previous studies presented a chatbot system with low-complexity models and were mainly about the user experience and rarely evaluated in regards to the chatbot's performance [10] [11]. Also, most research used various machine learning techniques, GD algorithm and natural language processing (NLP) algorithms. Therefore, to overcome this low-complexity, this study tends to use Neural Network (sequential models (RNN)) in developing a chatbot which offers a more intelligent system

2. Related Works

Within the field of mental health care, chatbots have been developed to act as a means of developing interpersonal capabilities as a component of a depression treatment regimen. This has led to the creation of a new avenue for the treatment of depression. In addition, research has been done on chatbots that are created with the express purpose of addressing difficulties that are associated with stress. It has been developed into a chatbot-based self-help software and given the name MYLO. It was discovered by Kamita *et al.* [12] that MYLO is effective at relieving pain, as well as depression, anxiety, and stress. In addition to this, it has been hypothesized that MYLO might be especially useful for improving one's capacity to find solutions to problems.

In addition, Ly *et al.,* [13] have developed a cognitive behavioural therapy-based automated conversational chatbot that they have dubbed "Woebot." This chatbot can be accessed through Facebook Messenger and engages in conversation with users. In this study, an evaluation experiment was carried out to see whether or not the "Woebot" was beneficial in reducing the number of depressed symptoms experienced by college students. The individuals' levels of depression symptoms were found to have significantly decreased, as demonstrated by the findings. The participants made the observation that the utilization of "Woebot" showed better responsiveness in comparison to conventional treatment procedures. The use of cognitive behavioural therapy (CBT), which is commonly used in the treatment of mental health issues, has been shown to be effective in the management of these conditions, according to previous study and published literature.

According to the findings of Abd-Alrazaq *et al.,* [14], there is a paucity of clinical outcomes that are associated with the employment of chatbots for the sake of mental health. The investigators counted a total of 41 unique chatbots that are used in the field of mental health. The majority of these chatbots are written as rule-based and stand-alone software, similar to Wysa and WoeBot. Chatbots are able to process the information provided by users and carry on discussions that are both responsive and guided in order to provide guidance to persons who are struggling with mental health issues. In most cases, automated systems will enquire on a regular rhythm about the behavioral patterns, cognitive processes, and emotional condition of an individual. Through the utilization of the accelerometer that is built into the user's mobile device, certain systems have the capacity to do movement tracking in a non-intrusive manner on the users of those systems.

Denecke *et al.,* [15] introduced SERMO, a mobile application that combines a chatbot and applies techniques from cognitive behavior therapy (CBT) to assist individuals with mental health disorders in managing their emotions and addressing their thoughts and feelings. SERMO was designed to help people with mental health conditions manage their emotions and address their thoughts and feelings. SERMO will ask the user questions regarding the activities and feelings that they experience on a daily basis. The lexicon-based approach and natural language processing are applied in order to automatically determine the core emotion of a user based on their natural language input. This is accomplished by analyzing the user's input. Depending on the particular emotion that is being experienced, SERMO will make recommendations for appropriate actions such as participating in activities or practicing mindfulness exercises.

It has been suggested by Oh *et al.*, [16] that psychiatric counseling could benefit from the use of a conversational service. This service makes use of tailored approaches to interpret counseling topics on the basis of a multi-modal approach, with a high level of natural language understanding (NLU) and emotion recognition. The techniques that were utilized make it possible to keep a continuous watch on emotional shifts while maintaining a high level of sensitivity. In addition, a workable strategy for addressing clinical psychiatric counseling emerges from the combination of the ethical judgment model and the case-based counseling response model.

A study was carried out by Park *et al.,* [17] with the intention of designing a conversational sequence for a condensed motivational interview that could be carried out via a text messaging application (chatbot) that was hosted on the Internet. In addition to that, the study wanted to investigate the ways in which graduate students deal with stress in their everyday lives. The authors used a succinct conversational sequence that adhered to the four core stages of motivational interviewing (MI). This sequence was purposefully created with varied permutations of motivational interviewing (MI) skills. In order to facilitate the transmission of conversational sequences, a research prototype called Bonobot, which is a web-based text messaging program, was developed. The application's primary goal was to improve user experience. Participants in the study were required to report having experienced stress as a direct result of their academic endeavors and were selected from a pool of thirty full-time graduate students. The participants' average level of perceived stress was 22.5 (with a standard deviation of 5.0), which indicates a significant level of stress.

EREBOTS is an agent-based framework that was established by Calvaresi *et al.,* [18] for the objective of facilitating the construction of chatbots. This framework is distinguished by the fact that it makes use of multiple front-end connectors and interfaces, such as Telegram, a specialized app, and a web interface, amongst others. Additionally, EREBOTS allows for the development of multi-scenario behaviors, such as preventative physical fitness, quitting smoking, and support for breast cancer survivors. The structure also includes online learning, as well as individualized chats and recommendations, such as boosting one's mood, dissuading one from seeking unhealthy foods, and maintaining one's equilibrium through physical exercise. Lastly, EREBOTS comes with a responsive multi-device monitoring interface that can be used by administrators and medical professionals. The findings imply that EREBOTS have been tested with regard to preserving their bodily equilibrium throughout times of social confinement, such as those that have resulted from the epidemic that is currently going on.

Hungerbuehler *et al.,* [19] created a totally automated conversational agent that they called "Viki." This type of agent is usually known as a chatbot. This chatbot's mission is to determine the possibility that employees would suffer from mental health conditions such as depression, anxiety, stress, burnout, sleeplessness, and work-related stress during their time with the company. The researchers carried out a cross-sectional examination in order to gain preliminary insights regarding a trial deployment in a small to medium-sized firm that included 120 employees. According to the findings, the response rate that was recorded was 64.2% (77 out of 120 total responses). The evaluation was started by a total of 98 employees, however only 77 people (representing 79% of the total) were able to successfully complete it. According to the criteria established by their separate questionnaire scores, the findings suggest that a sizeable majority of the participants exhibited low levels of anxiety (50%) and depression (57%), moderate levels of stress (46%), and subthreshold levels of sleeplessness (70%).

Anmella *et al.,* [20] developed a chatbot with the purpose of screening, monitoring, and mitigating the symptoms of anxiety and depression, as well as work-related burnout. Additionally, the chatbot was designed to recognize suicidal inclinations in patients from primary care and healthcare professionals. The researchers simulated Vickybot for a period of two weeks and utilized healthcare scenarios to replicate various clinical conditions of Vickybot. Throughout the simulation, the researchers ensured that the data was delivered and registered in an accurate manner. Within the framework of the simulation, the research involved a total of 17 HCs and a sample size of 13 people, of which 76% were female participants. There was a standard deviation of 9.7 years in age from the mean age of the participants, which was 36.5 years. It was discovered that the HCs were provided with 98.8 percent of the modules that were expected. The warnings about potential suicide attempts were picked up correctly. According to the findings of the research, Vickybot displayed a high degree of subjective UEI in terms of acceptability, usability, and overall satisfaction. On the other hand, it was discovered that the objective UEI measures, which include completion, adherence, compliance, and engagement, were quite low.

3. Methodology

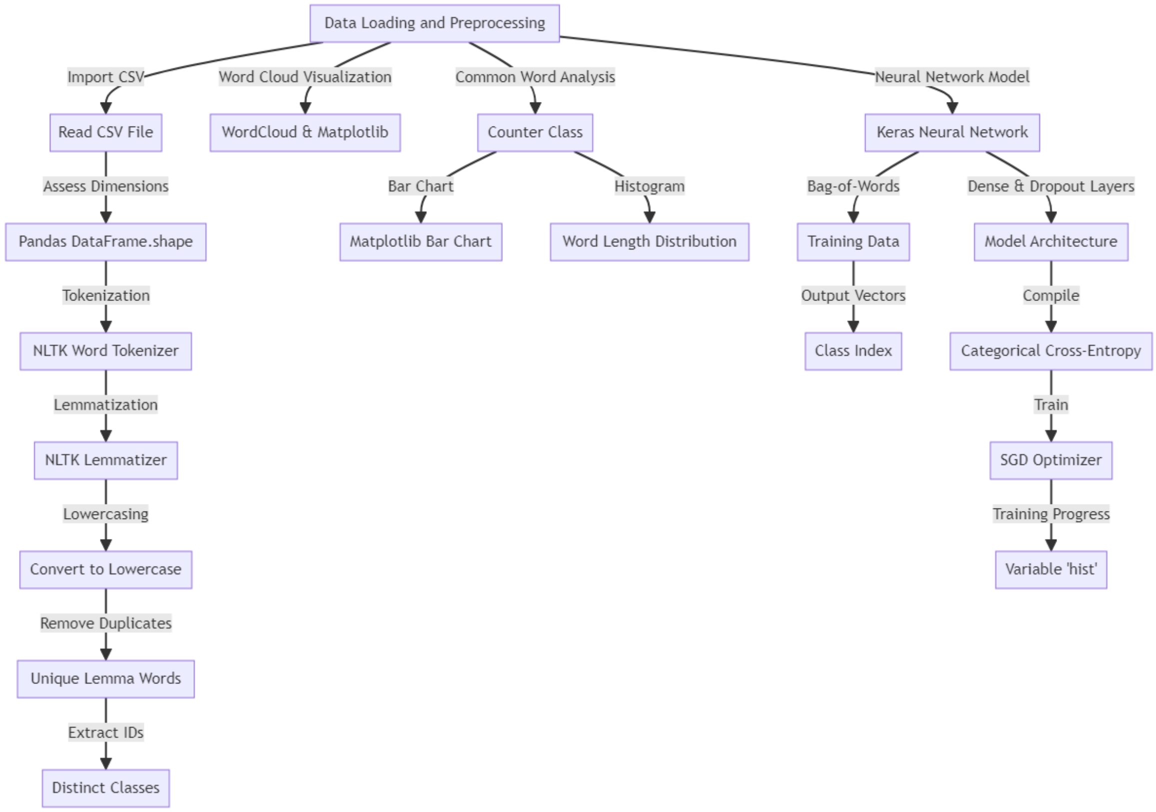

Figure 1: Design Flow Chart

3.1 Data Loading and Preprocessing

The dataset under consideration, accessible on Kaggle at the URL: https://www.kaggle.com/datasets/narendrageek/mental-health-faq-for-chatbot, consists of a collection of Frequently Asked Questions specifically related to the topic of Mental Health. The dataset has 98 items and is characterized by three columns. The dataset has three distinct qualities. A unique identifier, inquiries, and responses. The Unique_ID serves as the distinct identification for each individual enquiry. Regarding issues related to an individual's mental well-being, appropriate responses are provided for each inquiry. **The** necessary libraries such as Natural Language Toolkit (NLTK), Keras, Pandas, and others were utilized. The initial procedure was importing the dataset from a Comma Separated Values (CSV) file titled "Mental_Health_FAQ.csv" through the utilization of the read_csv() function provided by the Pandas library. The dimensions of the dataset were assessed by utilizing the shape feature of the Pandas DataFrame. The dataset underwent multiple preprocessing processes. The process of tokenization involved breaking down each question into separate words using the word tokenizer provided by NLTK. The process of lemmatization was employed to reduce words to their base form, and subsequently, all words were changed to lowercase. To generate a list of distinct lemma tied in words you words, any duplicate words were eliminated. The process involved extracting and subsequently appending question IDs to a collection of distinct classes.

3.2 Word Cloud Visualization

Through the use of the WordCloud and Matplotlib tools, a visualization of the most commonly used terms in the questions was created. The key terms in the dataset were summarized in a word cloud, making it easier to grasp the data's meaning at a glance.

3.3 *Common Word Analysis*

Using the Counter class in the collections library, how often each word appeared was counted in the questions. Through this research, we were able to isolate the most frequently used terms in the repository. The top N most frequent terms were graphically represented as a bar chart in Matplotlib. The length of each word in every question was calculated, and a histogram depicting the distribution of word lengths was generated. Word length distribution in the dataset was plotted as a histogram.

3.4 *Neural Network Model Creation and Training*

In order to train the model, the training data was produced by generating a bag-of-words for each question, denoting the inclusion or exclusion of terms from the lexicon. Output vectors were constructed in which a value of "1" was assigned to the index that corresponds to the class (question ID) of the question, while the remaining indices were assigned a value of "0". A neural network model was developed with the Keras package. The model's architecture consisted of dense units and dropout layers implemented for the purpose of regularization. The model was assembled utilizing categorical cross-entropy loss and trained employing stochastic gradient descent (SGD) as the optimizer. The progress of the training was documented in the variable named "hist".

4. Results and Discussions

4.1 Results

A. Exploratory Data Analysis

The analysis of word frequency in the questions reveals that the most commonly used terms are find, help, health, difference, information, care, and someone, among others. Figure 2shows the Top 20 Most Common Words

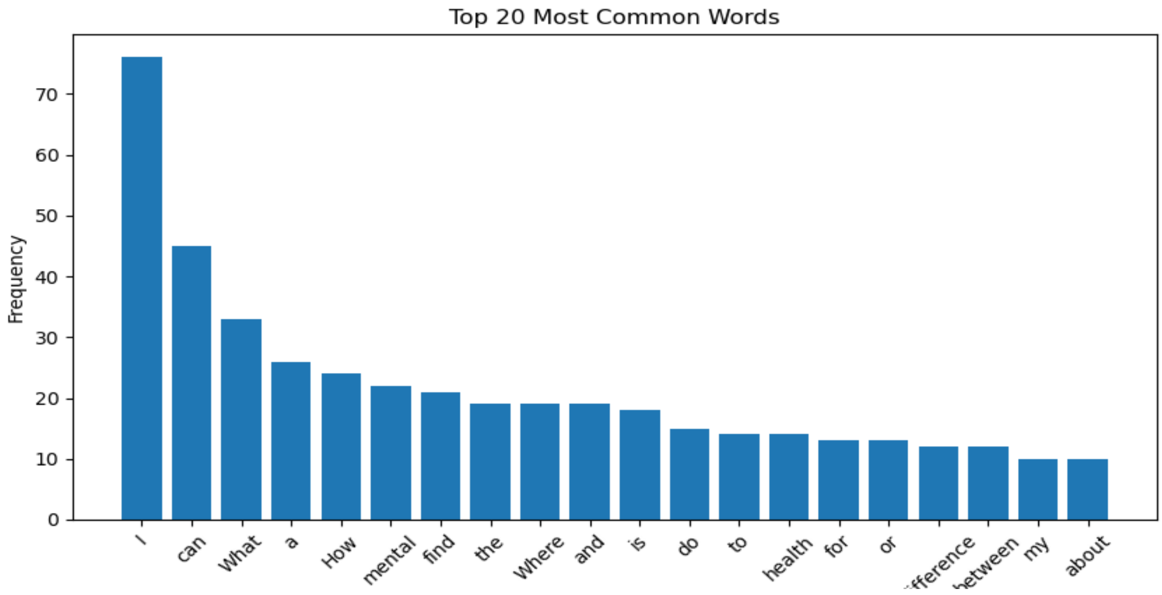

Figure 2: Top 20 Most Common Words.

There are some few common words in the questions and answers, the words are represented on the bar plot in Figure 2.

B. Model Building and Evaluation

```
Epoch 186/200
20/20 [==============================] - 0s 4ms/step - loss: 0.7734 - accuracy: 0.7755
Epoch 187/200
20/20 [==============================] - 0s 4ms/step - loss: 0.7987 - accuracy: 0.7755
Epoch 188/200
20/20 [==============================] - 0s 4ms/step - loss: 0.7420 - accuracy: 0.7449
Epoch 189/200
20/20 [==============================] - 0s 4ms/step - loss: 0.6010 - accuracy: 0.8571
Epoch 190/200
20/20 [==============================] - 0s 4ms/step - loss: 0.7014 - accuracy: 0.8061
Epoch 191/200
20/20 [==============================] - 0s 4ms/step - loss: 0.5872 - accuracy: 0.7857
Epoch 192/200
20/20 [==============================] - 0s 4ms/step - loss: 0.7251 - accuracy: 0.7959
Epoch 193/200
20/20 [==============================] - 0s 4ms/step - loss: 0.6004 - accuracy: 0.7551
Epoch 194/200
20/20 [==============================] - 0s 4ms/step - loss: 0.9680 - accuracy: 0.7143
Epoch 195/200
20/20 [==============================] - 0s 4ms/step - loss: 0.8691 - accuracy: 0.7041
Epoch 196/200
20/20 [==============================] - 0s 4ms/step - loss: 0.7204 - accuracy: 0.7959
Epoch 197/200
20/20 [==============================] - 0s 4ms/step - loss: 0.6995 - accuracy: 0.7857
Epoch 198/200
20/20 [==============================] - 0s 4ms/step - loss: 0.5310 - accuracy: 0.7857
Epoch 199/200
20/20 [==============================] - 0s 4ms/step - loss: 0.5523 - accuracy: 0.8469
Epoch 200/200
20/20 [==============================] - 0s 4ms/step - loss: 0.8582 - accuracy: 0.7245
```

Figure 3: The Result of the Model

Figure 3 shows the training progress of a machine learning model over 200 epochs, indicating the model's learning phase. Each epoch reports the time taken per step and two performance metrics: loss and accuracy. The loss metric, which should ideally decrease with training, represents the model's prediction error. The accuracy metric, expected to increase, shows the proportion of correct predictions made by the model. From the displayed output, the model's performance is improving over time, as evidenced by decreasing loss and increasing accuracy.

Figure 4 illustrates the progression of loss values throughout epochs ranging from 0 to 100. The findings indicate a negative correlation between the number of epochs and the magnitude of loss, suggesting that as the number of epochs increases, the loss decreases. This suggests that the model achieves a lower loss value as the number of epochs increases.

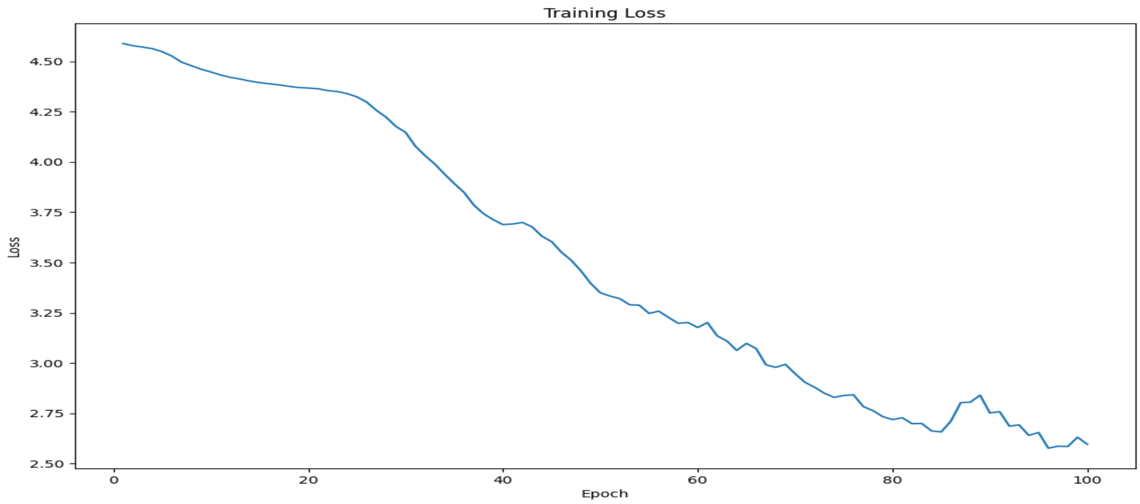

Figure 4: Training Loss Graph

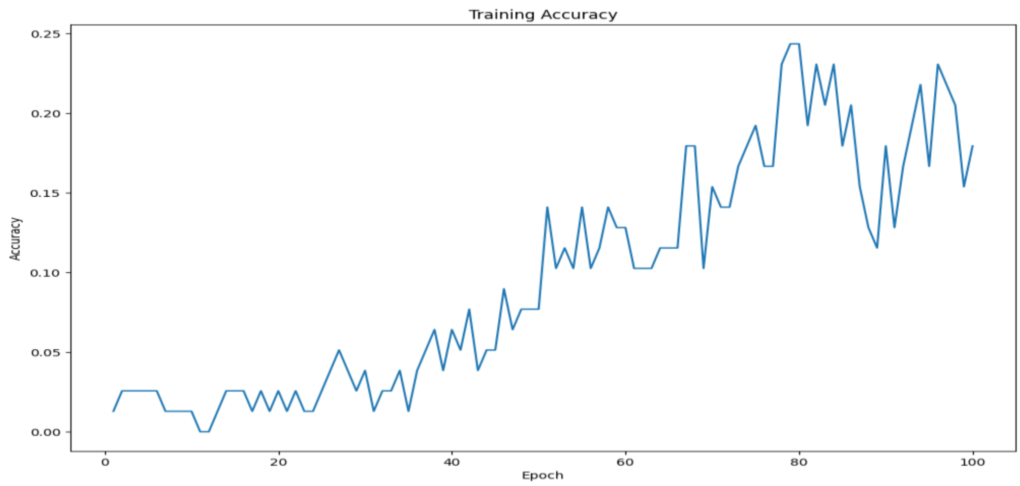

Figure 5: Training Accuracy Graph

The training accuracy as depicted in Figure 5 is seen to be somewhat low as a result of the utilization of a limited dataset for the purpose of validating the performance of the model. From Figure 6, as the number of epochs increases, the validation loss has a tendency to have higher loss values, although the training loss remains low with increasing epochs

C. Model Deployment

The implementation of the web-based chat paradigm utilized Flask, a widely adopted Python framework. The Keras and pickle library functions are utilized to load the chatbot model, intentions JSON file, and word dictionaries into the system memory. The preprocessing functions are responsible for preparing textual material in order to facilitate analysis.

(i) The predict_class function utilizes the loaded model to make predictions about the user query intent by employing the preprocessed text.

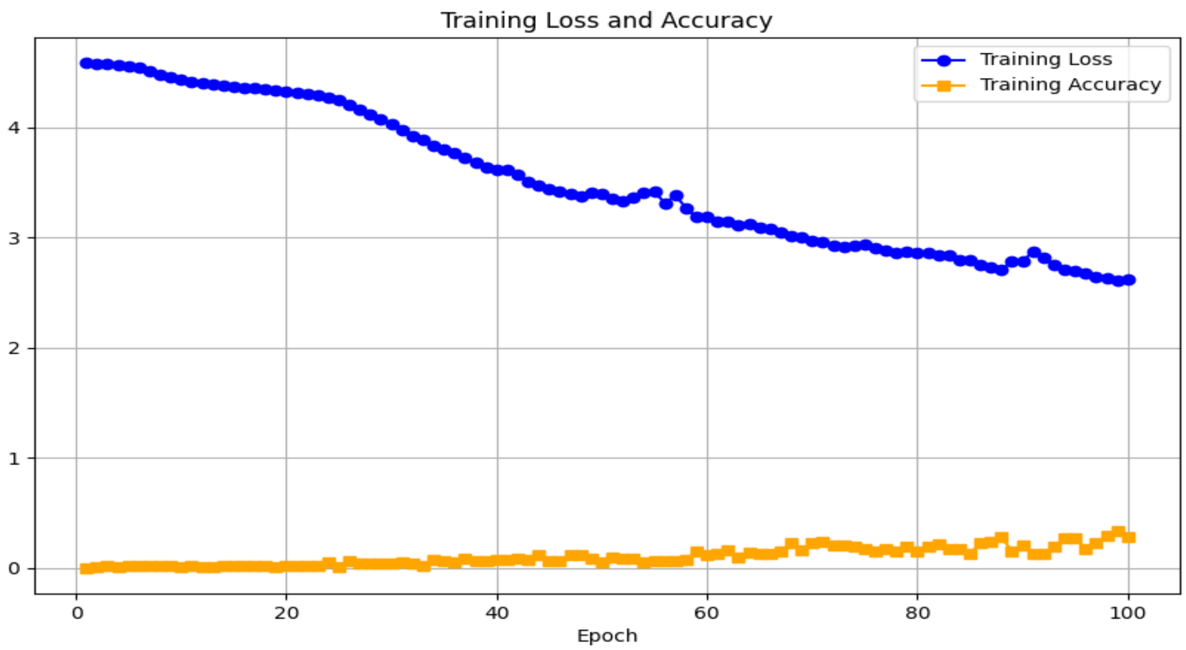

Figure 6: Training loss and Validation loss graph

(ii) The getResponse method is responsible for identifying the necessary intent and retrieving the corresponding response from the JSON file containing the intents.

The Flask application was initialized, and all routes were meticulously established to facilitate seamless navigation. The home route is responsible for generating an HTML template that serves as the graphical user interface (GUI) for the chat application. The /get route is responsible for receiving user inquiries and providing the corresponding response from the chatbot. The Flask framework was executed throughout the deployment process. This initial action initiates the user's default web browser and promptly presents the chat interface.

D. The Result of the Web Interface and Some Chat with the AI Chabot

The depicted image in Figure 7 is the initial interface of the deployed model on the internet, wherein the chatbot referred to as "Counsellor" introduces itself and provides a disclaimer stating that it is an AI tool designed to assist users, rather than a certified medical expert.

The result seen in Figure 8 presents the conversation that took place between the AI system and a user.

The start page

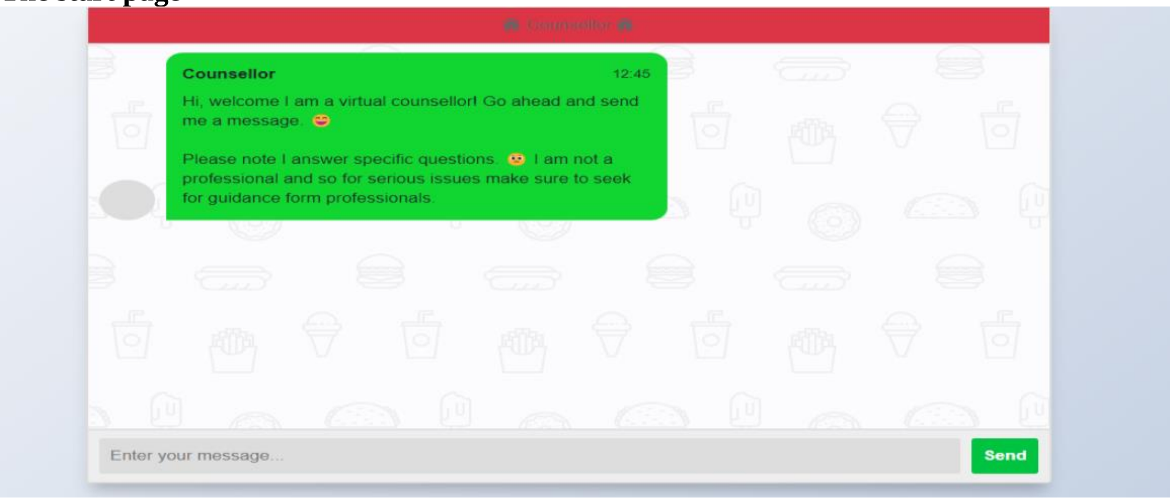

Figure 7: Start Page

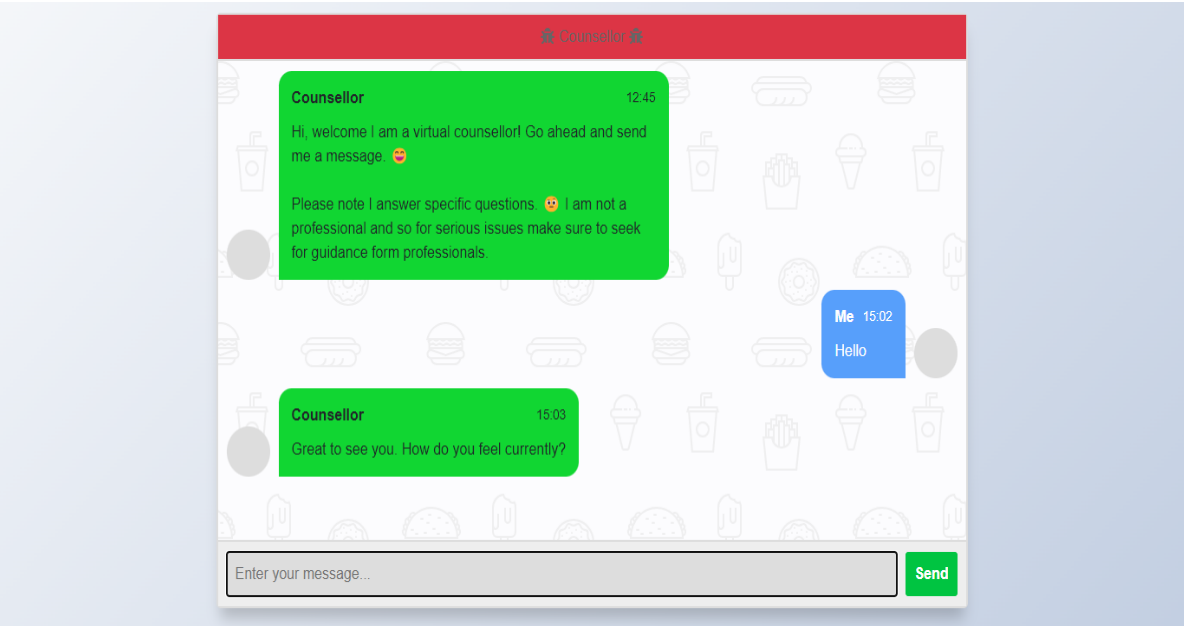

Figure 8: Dialogue from the AI chatbot and the User

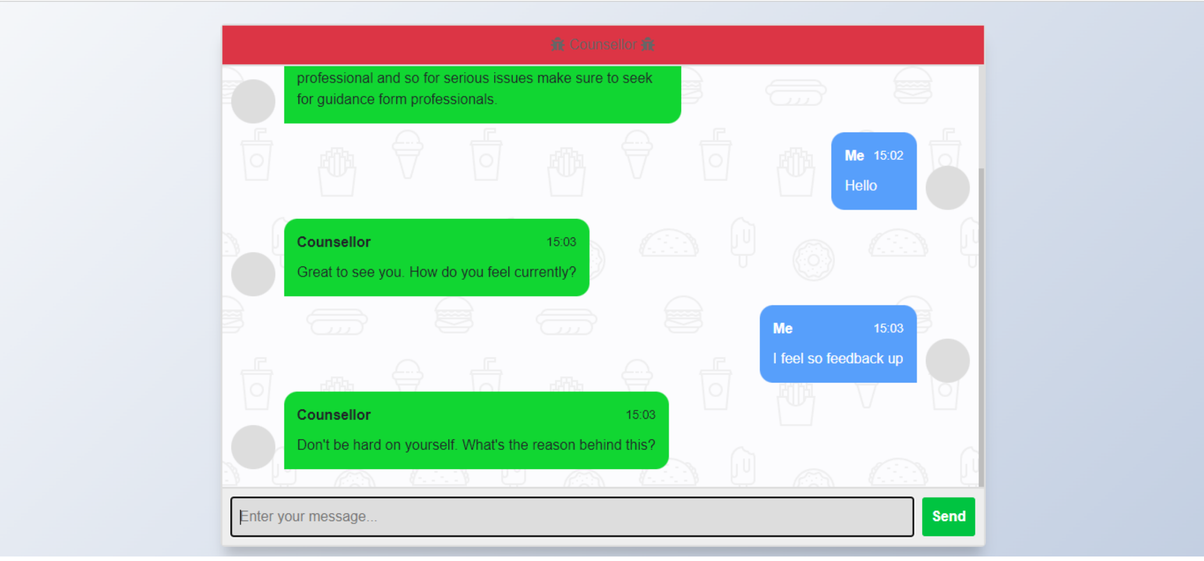

Figure 9: Dialogue from the AI chatbot and the user

The result in Figure 9 presents more conversation that took place between the AI system and a user.

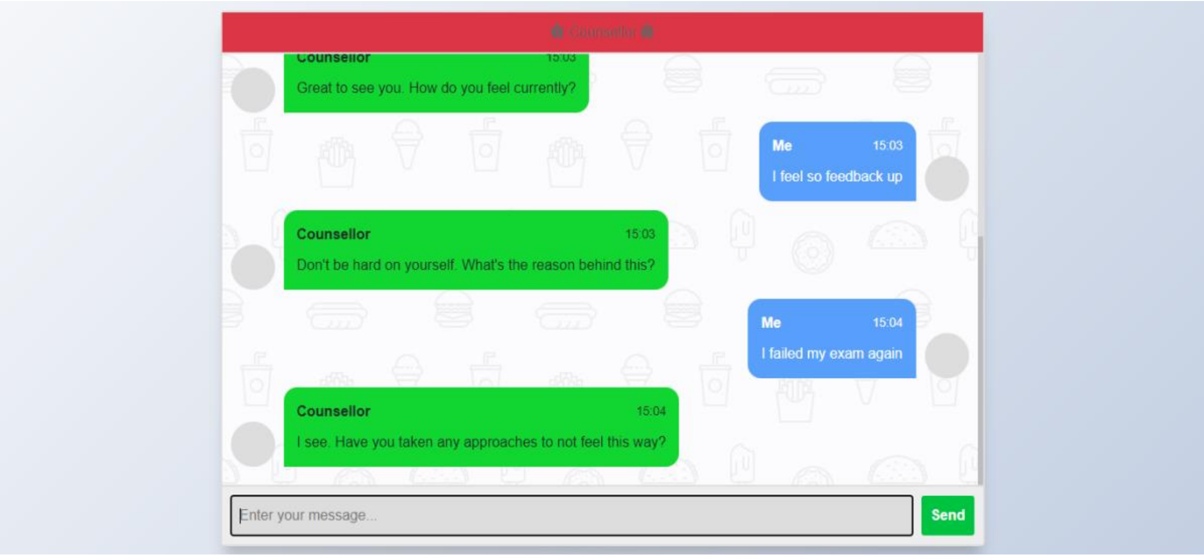

Figure 10: Close of the dialogue between the AI chatbot and the user

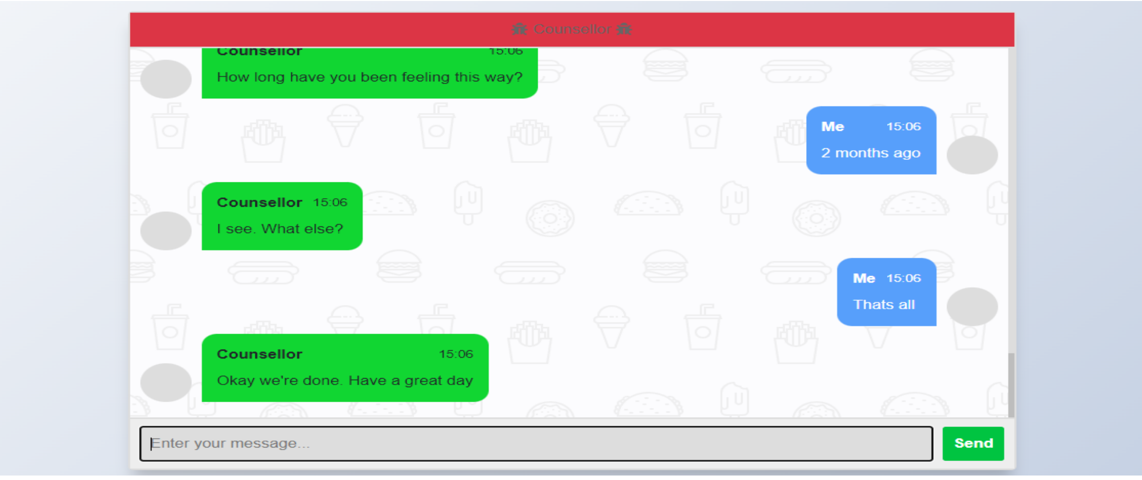

Figure 11: Dialogue from the AI chatbot and the user

The result displayed in Figure 11 illustrates the conclusion of the conversation between the user and the AI chatbot

4.2 Discussion

The eexploratory data aanalysis revealed that the most frequently used terms in the questions and answers were 'find', 'help', 'health', 'difference', 'information', 'care', and 'someone', among others. This helped in understanding the primary concerns and topics users might consult the chatbot for. The machine learning model was evaluated over 200 epochs. The key metrics monitored were loss and accuracy.

A notable finding was the negative correlation between the number of epochs and the magnitude of loss, which suggested improved model performance over time. As the training progressed, the loss decreased, and the accuracy of the model in making correct predictions increased. This demonstrated the chatbot's growing efficiency in understanding and responding to mental health queries. For deployment, the study utilized Flask, a Python framework.

The chatbot model, along with its intents and word dictionaries, were loaded into the system using Keras and pickle libraries. The 'predict_class' function of the model made predictions about user query intent using the preprocessed text, and the 'getResponse' method retrieved the appropriate response from the intents database. The Flask application was designed to provide a user-friendly graphical interface for interaction with the chatbot. The deployed chatbot, named "Counsellor", was presented on a web interface. The initial interaction page included a disclaimer clarifying that the chatbot is an AI tool and not a certified medical expert. The conversation examples provided in the study showcased the chatbot's ability to conduct meaningful dialogue with users, addressing their queries and concerns in a coherent and contextually appropriate manner.

5. Conclusion

Cutting-edge technology, such as an LSTM-based chatbot model, has the potential to mitigate mental health challenges. The seamless implementation of the concept implies its potential to assist individuals seeking mental health support. The methodology establishes a connection between technological advancements and the promotion of mental health awareness through the accurate categorization of user inquiries.

One notable advantage of the approach is in its capacity to comprehend challenges related to language and context, particularly in the setting of mental health discourse. The design of Long Short-Term Memory (LSTM) enables the model to effectively capture and comprehend the dependencies included in sequential data, hence facilitating its ability to comprehend user enquiries. Nevertheless, it is important to acknowledge that machine learning models has several limitations, one of which is the potential for producing inaccurate or misleading outcomes. It is recommended that improvement refining and enhancing the chatbot's capabilities by regularly updating the chatbot's knowledge base, therapy recommendations, and conversational abilities to ensure it remains relevant and effective.

References

[1] Health, T. L. G. (2020). Mental health matters. *The Lancet. Global Health*, *8*(11), e1352.

[2] Rathnayaka, P., Mills, N., Burnett, D., De Silva, D., Alahakoon, D., & Gray, R. (2022). A mental health chatbot with cognitive skills for personalised behavioural activation and remote health monitoring. *Sensors*, *22*(10), 3653.

[3] Maercker, A., Brewin, C. R., Bryant, R. A., Cloitre, M., Reed, G. M., van Ommeren, M., ... & Saxena, S. (2013). Proposals for mental disorders specifically associated with stress in the International Classification of Diseases-11. *The Lancet*, *381*(9878), 1683-1685.

[4] Regier, D. A., Kuhl, E. A., & Kupfer, D. J. (2013). The DSM-5: Classification and criteria changes. *World psychiatry*, *12*(2), 92-98.

[5] Oud, M., De Winter, L., Vermeulen-Smit, E., Bodden, D., Nauta, M., Stone, L., ... & Stikkelbroek, Y. (2019). Effectiveness of CBT for children and adolescents with depression: A systematic review and meta-regression analysis. *European psychiatry*, *57*, 33-45.

[6] Topol, E. J. (2019). High-performance medicine: the convergence of human and artificial intelligence. *Nature medicine*, *25*(1), 44-56.

[7] Fuad, A., & Al-Yahya, M. (2022). Recent developments in Arabic conversational AI: a literature review. *IEEE Access*, *10*, 23842-23859.

[8] Kretzschmar, K., Tyroll, H., Pavarini, G., Manzini, A., Singh, I., & NeurOx Young People's Advisory Group. (2019). Can your phone be your therapist? Young people's ethical perspectives on the use of fully automated conversational agents (chatbots) in mental health support. *Biomedical informatics insights*, *11*, 1178222619829083.

[9] Sweeney, C., Potts, C., Ennis, E., Bond, R., Mulvenna, M. D., O'neill, S., ... & Mctear, M. F. (2021). Can Chatbots help support a person's mental health? Perceptions and views from mental healthcare professionals and experts. *ACM Transactions on Computing for Healthcare*, *2*(3), 1-15.

[10] Skjuve, M., & Brandtzæg, P. B. (2018). Chatbots as a new user interface for providing health information to young people. *Youth and news in a digital media environment–Nordic-Baltic perspectives*.

[11] Vaidyam, A. N., Wisniewski, H., Halamka, J. D., Kashavan, M. S., & Torous, J. B. (2019). Chatbots and conversational agents in mental health: a review of the psychiatric landscape. *The Canadian Journal of Psychiatry*, *64*(7), 456-464.

[12] Kamita, T., Ito, T., Matsumoto, A., Munakata, T., & Inoue, T. (2019). A chatbot system for mental healthcare based on SAT counseling method. *Mobile Information Systems*, *2019*.

[13] Ly, K. H., Ly, A. M., & Andersson, G. (2017). A fully automated conversational agent for promoting mental well-being: A pilot RCT using mixed methods. *Internet interventions*, *10*, 39-46.

[14] Abd-Alrazaq, A. A., Alajlani, M., Alalwan, A. A., Bewick, B. M., Gardner, P., & Househ, M. (2019). An overview of the features of chatbots in mental health: A scoping review. *International Journal of Medical Informatics*, *132*, 103978.

[15] Denecke, K., Vaaheesan, S., & Arulnathan, A. (2020). A mental health chatbot for regulating emotions (SERMO)-concept and usability test. *IEEE Transactions on Emerging Topics in Computing*, *9*(3), 1170-1182.

[16] Oh, K. J., Lee, D., Ko, B., & Choi, H. J. (2017, May). A chatbot for psychiatric counseling in mental healthcare service based on emotional dialogue analysis and sentence generation. In *2017 18th IEEE international conference on mobile data management (MDM)* (pp. 371-375). IEEE.

[17] Park, S., Choi, J., Lee, S., Oh, C., Kim, C., La, S., & Suh, B. (2019). Designing a Conversational Sequence for a Brief Motivational Interview for Stress Management on a Web-Based Text Messaging App: Qualitative Case Study. *Journal of Medical Internet Research*, *21*(4).

[18] Calvaresi, D., Calbimonte, J. P., Siboni, E., Eggenschwiler, S., Manzo, G., Hilfiker, R., & Schumacher, M. (2021). EREBOTS: Privacy-compliant agent-based platform for multi-scenario personalized health-assistant chatbots. *Electronics*, *10*(6), 666.

[19] Hungerbuehler, I., Daley, K., Cavanagh, K., Garcia Claro, H., & Kapps, M. (2021). Chatbot-based assessment of employees' mental health: Design process and pilot implementation. *JMIR Formative Research*, *5*(4), e21678.

[20] Anmella, G., Sanabra, M., Primé-Tous, M., Segú, X., Cavero, M., Morilla, I., ... & Hidalgo-Mazzei, D. (2023). Vickybot, a Chatbot for Anxiety-Depressive Symptoms and Work-Related Burnout in Primary Care and Health Care Professionals: Development, Feasibility, and Potential Effectiveness Studies. *Journal of medical Internet research*, *25*, e43293.