Leveraging Chatbots for Mental Health Enhancement

Anthony Diaz
Department of Computer Science and Technology
Kean University
Union, NJ, USA
diazanth@kean.edu

Daehan Kwak
Department of Computer Science and Technology
Kean University
Union, NJ, USA
dkwak@kean.edu

***Abstract*—The COVID-19 pandemic has disrupted work, education, health care, the economy, and relationships, with some groups more negatively impacted than others. Many find themselves needing mental health help and advice, but they may run into issues getting help due to their location or a lack of funds. Mental health treatment can move to a virtual setting using an Emotional Assistant Chatbot to provide a supportive presence to service users, engaging them with a conversation at times when they feel low. The proposed chatbot would take a voice journal from the user daily and convert speech to text, as well as apply natural language processing techniques to provide the user with a mental health report and mental health advice. This is a tool that could also be used to track the mental health status of their patients to offer more accurate treatments. The user's speech is analyzed and associated with ten emotions such as anger and happiness, saved on a journal CSV file to create a mental health report. This study will conduct a literature review of current academic research regarding chatbots for mental health use and proposes the implementation of the mental health chatbot system.**

Keywords—Chatbot, Mental Health, NRC Emotion Lexicon, Natural Language Processing, Twitter.

I. Introduction

In everyday life, and especially in school/the workplace, people go through stress and many other things which can impact their emotional and physical state. The medically recognized effects of stress on the body are plentiful. There is medically reviewed evidence [1] which shows some of the negative effects of stress include increased depression, insomnia, high blood sugar, risk of heart attack, and more. All of these things are counterproductive to the well-being of an individual. The two most worrying effects of stress are the prevalence of increased depression and sadness. These two mental health states can lead to grave actions such as suicide. Therefore, it is in society's best interest to advocate, prevent or seek solutions to stress and continue to work towards making mental health treatment, such as self-help or prevention methods, more accessible.

While there are many ways to help increase one's mood and mental health state, most of these methods have seen their use limited due to COVID-19 and decreased social interaction, reduced social bonding, isolation, and loneliness impacting mental and physical health. While regular life proved stressful enough, the global pandemic led to heightened levels of stress, sadness, and hardship.

According to Panchal [2], "During the pandemic, about 4 in 10 adults in the U.S. have reported symptoms of anxiety or depressive disorder, a share that has been largely consistent, up from one in ten adults who reported these symptoms from January to June 2019." This data was taken from a Census Bureau Household Pulse Survey. That marks a 4x increase in negative emotions over the span of a single year. Sickness, death, inflation, and fear of the future have all led to this rapid increase. For students and employees, this stress increase is compounded even more. With the move to virtual learning and work, people have had to adapt to working conditions they would have never imagined. For those with a busy household, production and learning have been more difficult than ever. The long-term mental health effects of the pandemic are still unknown, but something must be done to combat the problem as it presently stands to reduce anxiety, and for mental disorders not to worsen.

Therefore, a solution to tackle this predicament is presented by implementing an Emotional Assistant Chatbot system that takes in the users' daily journal via voice, analyzes emotions based on Natural Language Processing, provides positive feedback on negative emotions when detected, and visualizes statistics on the emotions or feelings for easy interpretation for the user. The emotional support bot is expected to systematically improve the emotional health of a user over time. This bot will allow the user to see their emotional report over time, provide actionable advice depending on their emotional level, and be a useful tool for doctors to track the mental health status of their patients. Some of the questions answered by this research will include, "Can chatbots be used to treat mental health," and, "What are the benefits of using chatbots?" In section 2, we will conduct a literature review. A literature review is a collection of key sources relevant to the topic of chatbots in mental health and the conversation around the sources [5]. By conducting a literature review, we can understand the topic and create an effective mental health chatbot. Section 3 is about the system and design of the chatbot we created. That section will look at the different parts which make the bot, why they were used, and how they work. Section 4 shows the chatbot being tested using over 14,000 real tweets, to show its effectiveness. Sections 5 and 6 are the discussion and the conclusion, respectively. The paper finishes with future work in Section 7. The data sources for this study were compiled from various scholarly journals and publications about chatbots in mental health. The major findings of this work include the following:

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- One of the more prevalent limitations of chatbots is that they are not 100% accurate, and struggle with more nuanced speech.
- Chatbots are very useful when they are tools to be used by therapists, doctors, and qualified professionals.
- Chatbots are currently used in a supplementary fashion, and not as a primary care function in most cases.
- Current chatbot technology is best used as a preventative measure, to try and ensure that a patient's mental health does not get worse.

II. Literature Review

There are six main angles to view when looking at the use of chatbots to improve mental health. They are ethics, extreme cases, current chatbots, chatbots as a mental health treatment, chatbots compared to in-person care, and chatbot benefits. In this study, all these angles will be explored with current academic literature to determine where chatbot technology is now and if it is viable as a mental health treatment.

Mental health, in the sense of this research, refers to the emotional well-being of a person. This can be recorded in many ways. The most effective way to measure mental health is based on what the user/patient says. Someone or something must listen when a patient is speaking and expressing their mental health through emotions and direct statements. Since the dawn of time, that had been a human. That is where mental health chatbots come in. A chatbot accepts the user's speech or text and records their mental health level through algorithms and calculations. Next, we discuss the other facets of the combination of mental health and chatbots, and what studies have found about the pairing of both in current applications.

First, the ethics of chatbot usage is discussed. Mental health is a very human issue, and chatbots, however, are very much not human. Tackling emotional health problems with a tool that cannot understand mental health problems itself brings questions of doubt to chatbots. However, taking a step back allows one to see that chatbots can also serve as a bridge to more help; and in that sense, chatbots can be seen as very ethical. Kretzschmar found that, among young people, many believe that their issues are too personal to discuss with others [6]. Furthermore, young people in the study also spoke about how they valued privacy and felt that some information was too sensitive to share, even with a certified health professional. As mentioned earlier, chatbots are not human, and in this case, that makes them perfect for usability. Since they are not human, neutral, and not biased, they can safely take information from a user without judging them or exposing them by being anonymous.

Secondly, chatbots will eventually have to deal with some extreme cases. This can include blatant statements from the user regarding suicide and harm to self or others. Hosszu [4] looked at these types of cases specifically and looked at current chatbots such as Wysa and Woebot. They let a set of users in their 20s use the bots, and they collected data from the users, and the bots themselves. They found two main things from their research. The first is that current chatbots have many instances where they have a positive effect on the mental health of their users. More important, however, their second point was that current chatbots view human nature as rather negative. This means that chatbots currently fail to understand more nuanced human issues due to complexity and cannot label them correctly. In other words, current chatbots struggle to deal with extreme cases which have a lot of complexity and are not a clear-cut, such as suicide declarations by the user. This is one of the big challenges that chatbot technology must overcome.

In continuation, current chatbot technology exists and is very impressive. As mentioned, Wysa and Woebot are some of the current chatbot technologies available to the public. They are deployed to the public through mobile apps and have very good reviews. In a study by Hungerbuehler [7], they used a mental health chatbot named Viki, with 120 employees. They set out to measure the response rate amongst the employees. They wanted to see how the Viki chatbot would extract enthusiasm from the user. Their findings were that the Viki bot had a response rate of 64.2%. This is a high amount in a workplace environment, and by capturing the attention of most of the workplace, the Viki bot showed the continued rise in chatbot acceptance amongst people. Another study was run by Joerin [8], who looked at Tess, a bot deployed by X^2 and used by over 20,000 patients daily. From the data collected from the bot itself, it was found that continued led to double-digit percentage decreases in depression and anxiety. The truth is that current health bot technology is readily available. The current performance of these technologies shows that they can be helpful, even now. Over 4 current chatbots have been discussed so far and their abundance and accessibility will only continue to grow over time. This, in turn, means that research will have to grow in conjunction with the growth in the number of people who will begin to use mental health bots.

Furthermore, one must look at chatbots in general, as a mental health treatment. For that, there are a few studies that already show how they are being used in the mental health treatment space. Gamble looked at the use of mental health chatbot apps from a social informatics perspective [9]. They found that mental health chatbot apps currently have the infrastructure to support users and help healthcare providers give users a tool to use when they cannot reach a professional. The study also explains that in terms of mental health treatment, chatbots can only be supplemental or decisional support for the moment. Humans solve problems. Machines are the enablers, but without logic and situational context, technologies cannot replace humans. They still cannot be fully trusted to treat a patient's mental health issues alone. Another study was done by Cheng [10]. The study looked at 1,114 US participants who used chatbot services from top healthcare companies. Their findings were that chatbots had positively affected their users, but again, they still needed to be supplemented with professional care. Looking at the current deployment of chatbots in the mental health field, one can see that chatbots as mental health treatments still have some ways to go. Their current use in the field is supplemental, but not standalone. While looking at this, however, one has to consider that chatbots are fairly new technology, and there was a time in this millennium when such technology would have been deemed insane in the past. The fact that chatbots have been adopted by top healthcare providers, and are currently in use, shows that they are becoming useful assets to healthcare professionals. Further funding, as well as research within the mental health treatment field, will continue to find greater roles and uses for chatbots in mental health.

Moving forward, chatbots will be compared to in-person care. There are multiple pros and cons to each form of care. Overall, the best treatment option will differ from person to person. Some people prefer the physical presence of someone to talk to. Others are shyer, or more skeptical of talking to someone about their issues. In a study by Jacobs [11], they looked at Capability Sensitive Design. The study focused on how chatbots need to respect the social status of the user. The user is coming to the bot for a service, where the bot is the doctor, and the user is the patient. This is a role dynamic that needs to be taken seriously. In fact, this is one of the areas that need more research. There is not enough important research into the psychology of a user and their relationship to a mental health chatbot that they are approaching for help. As soon as the user sees the bot as helpful, beneficial, and solving problems, they are also becoming somewhat dependent on the bot for something important. This gives the bot lots of power over the user. When needing something as intimate as mental health help, the lines between technology and humanity can become blurred. This is seen already in the relationships between the average person and social media. In the same way that some people prioritize their social media image and life over their real life, that too can happen with a mental health patient possibly getting too comfortable with a bot and denying in-person care. This is detrimental to the development of mental health bots because it is seen from the previous studies that mental health bots are still not ready to accept such important responsibility, and fully carry out the responsibilities of being the main mental health provider to users. Therefore, as mentioned, there needs to be more research into the dynamics of the user and the bot including situational context, to prevent any negative effects on users and their bots. Currently, due to the limitations of mental health bots, in-person care is still superior.

Finally, it is important to look at all the recorded benefits of mental health bots in their current state. Dekker [12] ran a study where they deployed a mental health bot amongst students entering college. They targeted this demographic because they saw that it was a group that faced lots of stress and mental health issues. After using the bot amongst the students, they concluded that the chatbot helped them stay positive and avoid academic underperformance. This study shows a few things. The first is that chatbots can not only be deployed when there are issues but also in a preventive sense. The researchers detected students entering college as a risk group. Using chatbots, they were able to help these students in pivotal moments not only in their academic careers but in their lives in general. That shows that this technology is underrated and deserves more research attention. It can put many people on the right track in an accessible way. Another thing this study showed was that chatbots can do more than just make people feel temporarily better. Mental health is vital to all functions of a person, and what they do in their daily lives. The increase in academic performance helps showcase the holistic benefits of using a chatbot. Another study that shows the benefits of chatbots is from Deshpande [3]. The study tested the effectiveness of a chatbot they created. They tested it by running the chatbot through Twitter data and Reddit data. They found that the bot was 92.13% effective with Twitter data. With Reddit data, the bot was 97% accurate. By using social media site data, the study can capture an accurate representation of a large population of data, without actually needing real people. This shows that outside of bias and fringe cases, chatbots can be accurate in the conclusions they come to about the mental health state of a patient. This allows a user to feel a sense of confidence using a chatbot as a supplement to their actual healthcare provider. There are more benefits to using chatbots, and more benefits will continue to be found as more studies are conducted on specific cases, such as the Dekker study [12].

That is how current research looks at using chatbots to treat mental health. The six angles looked at were ethics, extreme cases, current chatbots, chatbots as a mental health treatment, chatbots compared to in-person care, and chatbot benefits. The angles each provided unique insight into what the current literature shows about the topic. This is a rapidly growing field of research, but the research that has been done already is meaningful. The hope is that this research will meaningfully contribute to the academia already published about mental health and chatbots and create new conversations.

III. System and Design

A. Chatbot System

When creating a chatbot, there are a few things to look for. Python was selected and the packages used were as follows: Google Text to Speech, PyPI speech recognition, NRC Emotion Lexicon, CSV, Plotly, Pandas, Seaborn, and Steamlit UI. All of these packages work in tandem to create the chatbot. The way the chatbot works is that the user chooses the time interval of the data they want to select, and they turn on the bot. After this, they listen to the bot and get its full range of commands. The bot can do a couple of things, but the main function is the “Hello” function. After the user says this word, the bot will ask the user, “How did their day go?”. The user then responds with an audio message which closes once they stop speaking and gets stored in the “Journal” CSV file. The bot will then react by telling the user their current emotional level and presenting graphs and charts that showcase their overall detected emotions throughout their journal, during the selected time period. The user/doctor would be able to see this data and make decisions based on it, although the bot provides some advice as well. The design of the chatbot can be broken down into the following sections: Voice-to-text, NRC emotion lexicon, and data visualization.

B. Voice-To-Text

The first main functionality of the chatbot is the voice-to-text functionality. This was built with Google text-to-speech and PyPI speech recognition. The speech recognition package detects the microphone of the user’s device so that the user can speak to the bot. The microphone use itself can be affected by background noise and microphone quality. In order to minimize this, we implemented a line of code that adjusts for ambient noise. This function comes with the PyPI speech recognition package and allows the user to communicate with the bot in different settings. Another important thing to note about the microphone is that it can be internal or external as the code automatically detects what the audio input device is.

The second part of this text-to-speech conversion is the GTTS package, which is used in two ways. The first way is to convert the text in the code into speech for the bot to speak to the user. The chatbot has hardcoded responses for every command/response that a user can give. The bot also states these commands at the start, but all of this is written. That is where Google text-to-speech comes in to convert the text in the code into speech that is outputted by the bot. This is done using a block of code (function) that repeats every time the bot must express one of its hardcoded responses to the user. This also includes the mental health advice the bot provides, to the questions that it asks the user. The second way that GTTS is used in the bot is in reverse to what was previously described. The user speaks to the bot, and their speech is converted into text. The user's speech needs to be converted into text so the bot can use it and analyze it.

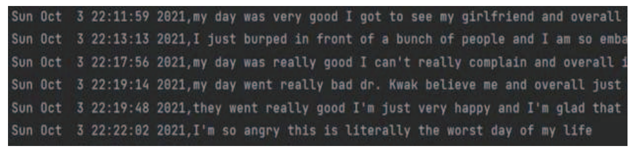
Fig. 1. User Voice Data Being Converted to Emotionally Rated Text

A few steps are needed to achieve the desired effect of converting the user's speech to text, as shown in Fig. 1. The first step is to collect the voice data from the user. This is done by launching the microphone for input every time the bot asks for something or asks for commands. The bot will then listen to the user and continue listening until the user stops talking for a whole second. This voice data is then saved as an mp3 file. GTTS transcripts the data in the mp3 file into text and this text is interpreted by the bot. The bot only saves the text into the CSV if it is a journal entry. Everything else is deleted, and the voice data mp3 is always deleted as there is no use after conversion. The journal CSV text can be run through the NRC Emotion Lexicon for emotion detection. There are many deep systems behind the NRC Emotion Lexicon.

C. NRC Emotion Lexicon

The second main portion of the chatbot is the lexicon. The NRC Emotion Lexicon [13, 14] is the workhorse of the chatbot. The lexicon contains 14,182 English words that are emotion tagged, and the lexicon can track two sentiments, (positive and negative), and 8 emotions, which are: anger, anticipation, disgust, fear, joy, sadness, surprise, and trust. All of this means that we can measure the emotional scores, and the most frequent emotions in a group of text, which in our case is the user's speech. These functions allow us to quantify what the user is feeling, without delving into machine learning, which has much greater complexity. The text of the user voice entries is stored in a CSV file labeled, "Journal". In the journal is the text transcription of what the user said, and the exact timestamp of when the user said it.

This journal is critical to the function of the chatbot. A sample of the journal is shown in Fig. 2. The bot does two things with the journal text data. The first thing it does is take the most recent entry. The most recent entry is plugged into the journal and then this text is analyzed by the lexicon. Each word in the user's voice data text is checked for emotion and if it is a positive or negative sentiment. Neutral words like, "and, is, or, the" are ignored. For example, if the user said, "My day was horrible, I cannot believe my mother would treat me like that," the text would tag as "negative" and the emotions found would be, "anger", "sadness" and "disgust". From that, the bot can understand that the user had a bad day and a negative entry.



```
Sun Oct  3 22:11:59 2021,my day was very good I got to see my girlfriend and overall
Sun Oct  3 22:13:13 2021,I just burped in front of a bunch of people and I am so emba
Sun Oct  3 22:17:56 2021,my day was really good I can't really complain and overall i
Sun Oct  3 22:19:14 2021,my day went really bad dr. Kwak believe me and overall just
Sun Oct  3 22:19:48 2021,they went really good I'm just very happy and I'm glad that
Sun Oct  3 22:22:02 2021,I'm so angry this is literally the worst day of my life
```

Fig. 2. Journal CSV file with User Entries

Nevertheless, how does this process work for the entire journal? The same way the bot plugs in the single entry and analyses it, for the overall journal data set, the whole journal is plugged into the NRC Emotion Lexicon. By doing this for a specified time interval, we can notice patterns in the user's mental health state. If over the span of a month, the user has a high frequency of words tagged as "anger" and "negative", we can deduce that they may need help. This is where the bot presents graphs and tables to the user about each emotion and how many times it has been tagged. The user will then be asked to look at their "negative" rating and state it to the bot. The bot follows up on this by asking for this negative rating and then offering mental health to the user. For example, if the user has a negativity percentage of 30%, the bot will say: "You are at a 7 out of 10 on the emotional distress scale. You have clear grievances. Try taking a few deep breaths, reflecting on the situation, and taking a step back to relax."

D. Data Visualization

The third main portion of the chatbot is the visualization of data and the UI. This is accomplished using Pandas, Seaborn, Plotly, and Streamlit UI. Pandas is used to create a table that stores each emotion, and the number of times each emotion was tagged or found in the journal. Plotly is used to create a bar graph and pie chart of the user's emotional report. Seaborn is used for formatting and colors in the pie chart and bar graph. Streamlit UI is the user interface of the chatbot. In Streamlit, the user can choose when to turn the bot on and off, and the time interval by which the data will be extracted from the journal CSV file. The Streamlit UI also shows all the text spoken by the bot, as well as all the charts and graphs that the bot produces, shown in Fig. 3. This UI is intuitive for a few reasons. One of these is that it is simple looking so it is highly accessible to all users. The second reason is that it is not data-intensive so it can be run on almost any device. The third reason the Streamlit UI was used is that it is highly compatible with all the parts of the Python Chatbot. It displays the text said by the bot and the data graphs/charts that the user needs access to.

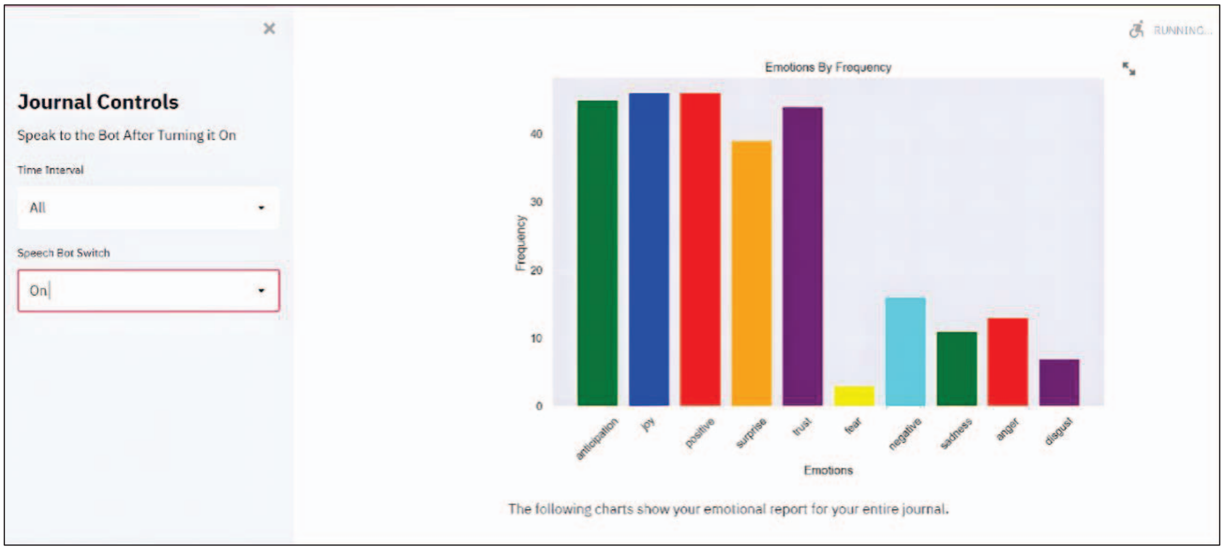


Fig. 3. Program UI and Sample Graph

As for what is shown to the user, there are a total of three data tools that the user will have access to. The first is a chart that shows the frequency of each emotion. This is followed up by a pie chart which each emotion and the percentage of their frequency in relation to the other emotions. The final tool shown to users is a bar graph which shows the same data as the pie chart but in a different format. As mentioned previously, the user can then look for the "negativity" rating and mention it to the bot to receive mental health advice.

IV. Evaluation

To evaluate the chatbot and lexicon's effectiveness, we used Twitter data and collected 14,694 tweets related to the COVID-19 pandemic. This data was used to act as the "journal" CSV file of the chatbot. In doing this, a simulation of 14,694 entries was created. Fig. 5. shows two examples of these tweets, one being positive and the other being negative. Fig. 4. shows the results of tweets being used in the chatbot. The findings indicate a high frequency of "fear" and "negativity" from the pandemic-related tweets which was to be expected. Surprisingly, however, the highest frequency sentiment was positivity, which was tagged 13,145 times by the NRC EmoLex which shows a couple of things. The first is that users vented their frustrations and worries through Twitter, leading to a spike in negativity and fear. The second takeaway from this is that despite the rise in negative sentiment, and more so as a result of the negative sentiment, positive sentiment increased as well, as people used Twitter to spread hope and optimism. The use of Twitter to vent grievances and boost mental health through positivity is exactly what this chatbot is trying to accomplish as well.

	Emotion	Frequency
0	trust	7036
1	negative	8117
2	positive	13145
3	sadness	3958
4	joy	7048
5	anticipation	6727
6	surprise	2795
7	fear	6712
8	anger	2505
9	disgust	1602

Fig. 4. Results of Twitter Data

V. Discussion

Overall, Chatbots are indeed viable for use in mental health treatments. Using a chatbot such as this one is a great way to track the user's daily emotions over time. This can be used to track trends or provide advice to improve the user's mental health. These findings are promising, however, there are two caveats. The first is that mental health chatbots are still not 100% accurate, which also means they are less reliable than a human professional. The second is that chatbots such as this one that does not use machine learning struggle to find out the nuance in speech and cannot, for example, detect the stress or the tone in a person's voice. The words are taken literally, and at face value.

This study aimed to look at the current state of mental health chatbots and how they can be better accepted and improved. The results from using a chatbot with Twitter data have shown where chatbots are in a technical sense. With the world advancing at such a rapid pace, and the human mind being asked to think about more things daily than ever, it is important to remember that mental health is key to a person's well-being and success.

```
please corona, dont make us cancel summer 2020😩🙈
 [('negative', 0.5), ('sadness', 0.5)]
 {'negative': 1, 'sadness': 1}
```

Fig. 5. Negative Tweet Entry

Mental health includes our emotional, psychological, and social well-being as everything starts to become digital, there is no reason for mental health treatments not to follow suit and become easier to access digitally, as the world becomes digital. While great strides have been made in chatbot technology and mental health treatments, there is still much work to be done.

The key findings of this research, when compared to the literature previously discussed, reveal many parallels. Some of these included the statements about chatbots having difficulties with nuance and worries about privacy. This is similar to Hosszu [4], which stated that many viewed chatbots as "corporations offering free services on the exchange of privacy and digital self." (p. 8). In the existing literature, privacy shows up as the number one issue. At the end of the day, this was to be expected. The nature of mental health issues is that for someone to receive treatment, users should be transparent. They would have to open up and become vulnerable. It is difficult enough to get people to open up to other people, and transparency is a keyway to creating trust. With chatbots, patients may feel like they can trust technology less, as they do not have a physical person making judgments that they can feel or see when they are talking about their personal or confidential problems or issues.

VI. Conclusion

The literature review found that chatbots are being used in health care, but there are some limitations. The limitations include the inability of current chatbots to correctly label more nuanced speech and not being 100% accurate. This background knowledge led to the creation of the Python Emotional Assistant Chatbot. Using NRC Emotion Lexicon, the bot can take a patient's words and give them emotional ratings. The NRC emotional lexicon consists of 14,182 English words that are tagged by a total of 10 different emotions. The proposed bot asks patients, "how their day went". Patients then proceed to speak to the bot, and their speech is converted into text, which is stored in a "Journal" CSV file. The NRC Emotion Lexicon is used to assign emotional ratings to a patient's words. From there, data visualization of the patient's emotional ratings is done with Pandas and Plotly. The patient is presented with this data, as well as some recommendations from the bot, based on the amount of positive and negative sentiment found in the patient's words. The chatbot's efficacy was further tested with the COVID-19 Twitter data. The results showed that the bot was able to identify high levels of "fear" and "negativity" from the 14,694 COVID-19 tweets. From this research, we have seen that chatbots are fit for use as tools by therapists, doctors, and qualified professionals. Chatbots are most beneficial when used in a supplementary fashion, and not as a primary care function. Chatbots are not yet capable of being used without the supervision or guidance of an actual healthcare professional, due to the limitations that were previously mentioned. Ultimately, chatbots would best be used as a preventative measure before a patient's mental health worsens.

VII. Future Work

The chatbot implemented in this paper has plenty of room for improvement and iteration. Future work on the Emotional Assistant Chatbot will include making the chatbot more robust and testing the chatbot on actual people. In order to make the chatbot more robust, we can investigate switching the NRC Emotion Lexicon to actual machine learning models [15-18], provide model-based recommendations [19], and provide topics [20] and summarization [21] from the journal. This would allow us to detect emotions in how words are spoken, which adds another layer to the accuracy capabilities of the chatbot. As for testing the chatbot on people, we can create a focus group and have them use it for a month and collect data to be analyzed.

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