JoyBot: RASA-Trained Chatbots to Provide Mental Health Assistance for Australians

Mary Adewunmi, Adish Ashraff, Tanya Dixit, Nikhil Shrestha, Veronica Gail Medrano, Bhushan Chougule*, Ahmed Fahim, Navaneeth Tirupath, and Sudha Sushma

***Abstract*—The project aims to boost the mental health of Australians using RASA-trained chatbots. JoyBot was trained with a hugging-face classifier, developed with RASA (Receive, Appreciate, Summarize, Ask), Docker and deployed with Stream-Lit. The EDA results showed that long-term health condition, Family type, Job status, House loans types and location of Australians had a significant effect on Australians' psychological distress level during and after the COVID lockdown, the hugging face transformer classified with Sentiment_VADER, 96% negative and 4% positive with candidate_labels: "Panic", "Anger", "Sad", "Happy", "Brave". We deployed Joybot with Streamlit and tested it with Intent Prediction Confidence Distribution showed that chatbot conversation was predicted correctly with 1. JoyBot would serve as a helping hand for Australians, guide them through Frequent Answering Questions (FAQ) and a directory for every Psychologist, thereby reducing the overall workload on the Mental health sector in Australia.**

***Index Terms*—COVID-19, mental health, Australians, RASA, Sentiment_VADER, Streamlit**

I. Introduction

This paper aims to outline the design and develop a chatbot for boosting the mental health of Australians and the expected outcomes. The research objectives (ROs) in this section, on the other hand, were to identify and discuss how mental health could be assisted with a chatbot in Australia (RO1); Examine the level of health challenges in Australia (RO2); speak with mental health professionals, and learn critical measures to preserving overall well-being (RO3); Create a prototype chatbot or web tool to assist people in sticking to a healthy routine (RO4); Test the prototype to see how it affects the user's experience (RO5). There are ten more sections after the introduction. The following section is based on what has been done in Australia regarding Mental Health Social Support (MHSS) report. Related research that this project entailed published papers on similar themes context. The chosen research method was reviewed. After that, a provisional model for chatbot project implementation was proposed based on concepts and success characteristics found in the literature and current models. Based on the findings of the Sentimental analysis of the case study, this was implemented and developed in the following section, and the result was evaluated. The results section preceded the conclusion, acknowledgement, ethical concerns, references, and appendices.

II. Background and Current Practices in Australia

COVID-19's potential to affect mental health and wellness was recognised early in the pandemic (WHO 2020). Aside from the risk of getting the virus, several procedures needed to stop it from spreading were also likely to influence mental health (NMHC 2020) significantly. From March 2020, widespread movement restrictions, social distancing techniques, and physical isolation, known as' lockdowns,' were imposed [1]. Many Australians' mental health has been harmed by the unexpected loss of job and social connection, the added stressors of moving to remote work or schooling, and, more recently, the effects of sudden, localised 'lockdowns' to prevent further breakouts. As a result of the pandemic, stress, bewilderment, and anger are widespread. While many people may not have long-term mental health issues, COVID-19 has the potential to contribute to or aggravate long-term mental disease [2]. Many researchers acquired evidence of increased psychological suffering during the epidemic during 2020 and the first months of 2021. While there was an increase in the use of mental health services and psychological distress in 2020 around the world [3], COVID-19 was linked to an increase in suspected suicide deaths from a mental breakdown in Australia [4]. The use of mental health services continued throughout 2021 in other parts of the world [5] while a range of mental health-related services provided by various levels of government was available to support Australians with mental health concern, as mentioned in other parts of Mental Health Services in Australia (MHSA) [6]. During the COVID-19 pandemic, the AIHW has been aiding the Australian Government Department of Health in curating, analyzing, and reporting on mental health-related service activities since April 2020. Data from the Medicare Benefits Schedule (MBS), Pharmaceutical Benefits Scheme (PBS), crisis and support organizations (Lifeline, Kids Helpline, Beyond Blue), and analysis of upcoming research findings are presented in two dashboards

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Mary Adewunmi is with SPIS, NACETEM, Lagos, Nigeria and Department of Medical Studies, University of Tasmania (UTAS), Hobart, Australia (e-mail: mary@moaanalytic.com).
Adish Ashraff is with Aigility, Australia (e-mail: adish.ashraff@gmail.com).
Tanya Dixit is with Australian National University(ANU), Australia (e-mail: Tanya.Dixit@anu.edu.au).
Nikhil Shrestha is with HDFC Bank, India (e-mail: n.shrestha17@gmail.com).
Veronica Gail Medrano is with Cascadeo Corporation, Phillipines (e-mail: nicamedrano98@gmail.com).
Ahmed Fahim is with University of Dhaka, Dhaka, Bangladesh (e-mail: afahim03@yahoo.com).
Navaneeth Tirupath is with OMDENA-Australia chapter, Australia (e-mail: navant@gmail.com).
Sudha Sushma is with Maharaja Surajmal Institute of Technology, New Delhi, India (e-mail: sushma.nippani2000@gmail.com).
*Correspondence: buchougule@outlook.com (B.C.)

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namely a national version and a jurisdictional version that focuses on service activities in New South Wales, [7] Victoria, and Queensland [8]. In addition, the AIHW has assisted the governments of New South Wales, Victoria, and Queensland in providing detailed statistics on the usage of mental health services. This, crucially, entails a two-way data exchange with the Australian government. The mental health COVID-19 reporting dashboard is in two versions [9]. This has been managed by 21 million MBS- subsidised mental health-related services processed between March 16, 2020, and September 19, 2021. MBS mental health services delivered through telephone or videoconference peaked in April 2020 [10], when telehealth accounted for nearly COVID-19 limits were first implemented in March 2020, the volume of mental health-related PBS medicines dispensed increased, then dropped in April 2020 [10]. Weekly volume increased from mid-May 2020 to early-August 2021, compared to the same week the previous year. These trends were noticed in all jurisdictions. In the four weeks leading up to September 19, 2021: Lifeline had many historical record-breaking daily call volumes, with 96,273 calls offered, up 14.1 per cent and 33.1 per cent, respectively, from the same periods in 2020 and 2019. In the same periods in 2020 and 2019, the Kids Helpline got 32,572 answered contact attempts, up 4.6 per cent and 16.7 per cent, respectively [10]. Beyond Blue got 27,099, half of all MBS mental health services. 37.0 per cent of MBS mental health services were delivered via telehealth [11]. COVID- 19's unpredictability, dread of long-term health repercussions, remorse, and suffering in isolation all had a significant impact on mental health, according to our findings and to deal with the psychological effects of the pandemic, clinical and public health measures are required [12]. At the same time, rich countries have approximately nine (9) psychiatrists per 100,000 [13]. It is challenging to give mental health interventions utilizing the one-on-one traditional gold standard approach due to a scarcity of mental health resources [14]. Mental health services do not reach around 55 per cent and 85 per cent of people in industrialized and developing countries, respectively, according to the World Health Organization [15]. Suicidal behaviour may result from a mental health service shortage, increasing mortality [16]. Due to a shortage of mental health workers, technological innovation has been used to satisfy the requirements of people impacted by mental health issues. This project aimed at building Chatbots to ease the ongoing stress from the Australian health sector. This solution is famous for people's self-disclosure of personal experiences, emotions, and feelings [17]. Chatbots have much potential in the mental health area because getting one's thorough self-disclosure is crucial for mental health experts to comprehend people's mental status.

III. Related Works

This section was structured into past work done on Chatbots, their uses for Mental health, and the methods used in the project implementation.

A. *Chatbots for Mental Health*

In the field of mental health care, chatbots are starting to develop. One-way chatbots can help healthcare workers is by diagnosing and triaging persons with mental health issues, which can help prioritise in-person services for those who need them the most. This virtual assistant can be used for patients with dementia, substance misuse, stress, depression and suicide, anxiety disorders, and PTSD. In this scenario, people interact with the chatbot as if it were a human being. The chatbot recognises the user's symptoms, predicts the disease, proposes treatment, or informs the patient about the diagnosis through a series of questions. Using AI [18] for diagnostic reasons can help identify those at risk, allowing for early intervention and reducing the possibility of future issues. Even if chatbots don't provide diagnoses, they can help boost involvement with mental health examinations, increasing the chances of discovering people who need help. The most typical use of chatbots in DMHIs is for content delivery.

While chatbots cannot replicate traditional psychotherapy, they may be able to deliver psychotherapeutic therapies that do not require a high level of therapeutic skill [19]. The most frequent and well-studied chatbots use cognitive behavioural therapy (CBT) principles; one meta-analysis indicated that CBT was used by 10 out of 17 chatbots [20]. Woebot [21], for example, uses NLP to deliver CBT to users via instant messaging, emulating human clinicians and social dialogue [22]. Other chatbots, on the other hand, use various therapeutic techniques, including acceptance and commitment therapy and mindfulness [23]. Wysa, an 'emotionally intelligent' chatbot, uses CBT, dialectical behaviour therapy, motivational interviewing, and other therapeutic approaches. Some chatbots, such as Vivibot, which helps young people learn positive psychology skills after cancer treatment to support anxiety reduction, have been developed for more specific applications.

In contrast, others, such as MYLO, use general self-help strategies when users are in distress and work toward suicide prevention [23]. It can also be utilized for symptom management and screening. Chatbots may also track symptoms and behaviours (such as physical activity, sleep hours, and time spent on social media). Chatbots are now utilized as personal health assistants to encourage well-being and mental health check-ins during and after interventions [24]. Chatbots can help users transfer therapeutic content into their daily lives, assess progress, and provide individualized support by delivering additional mental health resources in this role [25]. AI can also help in the personalization of care by allowing for more efficient storage and processing of user data, allowing users to comprehend better when symptoms flare up or decline. As a result, people without access to a mental health professional may be able to help their symptoms better and reduce their risk of relapse [26]. This management and screening can be employed in outpatient settings or following typical in-person interventions.

Chatbots could help clients sustain treatment benefits by reminding them of skills and practices (e.g., medication adherence, check-ups, exercise, and so on) [27]. People who live in rural areas or who work shifts may have difficulty getting appointments for mental health care, and chatbots could be a viable answer [28]. Woebot [29], a chatbot therapist receiving two million messages weekly, has recently garnered headlines. Students who used Woebot had dramatically reduced symptoms of depression within two weeks, according to a randomised control trial conducted at Stanford University. Tess, created by clinical psychologists at the x2-AI firm, provides support through Cognitive Behaviour Therapy (CBT), Solution-focused Brief Therapy (SFBT), and mindfulness [30].

B. Mood Classifier using Hugging Face Transformer

Transformers provides APIs that allow you to rapidly download and utilise pre-trained models on any text, fine-tune them on your datasets, and then share them with the community on our model hub [31]. Thousands of pre-trained models are available in Transformers to execute tasks in various modalities, including text, vision, and audio. These models can be used in over 100 languages for text classification, information extraction, question answering, summarisation, translation, and text production [32]. Images for picture classification, object identification and segmentation, audio for voice recognition and audio classification, table question answering, optical character recognition, information extraction from scanned documents, video classification, and visual question answering can be trained with transformer models [33].

C. RASA

Jiao [34] introduced RASA, pair of tools, Rasa NLU and Rasa Co, which are open-source python libraries for building conversational software. They aim to make machine-learning-based dialogue management and language under- standing accessible to non-specialist software developers. Regarding design philosophy, we aim for ease of use and bootstrapping from minimal (or no) initial training data. Both packages are extensively documented and ship with a comprehensive suite of tests.

IV. Datasets

Four groups of data sets were used for this project:

A. Official Datasets

Three Forums/Surveys were found: COVIDiStress, ABS Survey and Social Impact Survey. COVIDiStress was the official data used for EDA. 228,874 tweets were scraped on Jan 22nd, 2022, from twitter with 24 columns applying the tweepy python method using the keywords shown in diagram 1. The corpus was pre-processed and cleaned using NLTK methods. The dataset's attributes, as seen in diagram 2. per cent, stopword and stop word per cent using NLTK. Using average perception tagger and Punkt library, others were deducted like the Noun count, Pronoun count, proper noun count, modal, verb present, verb past, adjectives count and word token count.

B. Counsel Chat Datasets

This contains conversations and suitable replies from mental health professionals like therapists.

C. Social Media

Twitter was scraped using SNScrape, which allows scraping Twitter for a date range and location, using specific keywords relevant to Mental Health AUS.

D. Forums

Surveys/ interviews/ forums where people openly share their concerns

1) Reddit
2) FAQs

Keywords
abuse, addiction, angst, bipolar, circuit breaker, community cases, coronavirus, counselling, counsellor, covid, crisis, dead, death, dependence, depression, disorder, drugs, dysthymia, emotion, fatality, rate, fight, hbl, heightened alert, help, home based learning, imh, insomnia, irritable, isolation, jobseeker, job keeper, jobmaker, job, insecurity, lockdown, loneliness, lonely, melancholia, mental health, mental illness, mood disorder, mood swings, national emergency, neurosis, no motivation, outbreak, overwhelmed, paranoia, phobia, post-traumatic stress, disorder, pre-covid, psychologist, quarantine, redundancy, restriction, retrenchment, rona school closure, self-esteem, self-harm, social anxiety, socialize, sos, stay home notice, stood down, stigma, stress, suicide, therapy, tighter measures, tired, toxic, trapped, trauma, unalive, uncertainty, variant, well-being, wfh, work from home.

Diagram 1. Keywords for scraping data.

Attributes
url, date, content, rendered 'Number', 'Unnamed: 0', 'id', 'user', 'replyCount', 'retweetCount', 'likeCount', 'quoteCount', 'conversationId', 'lang', 'source', 'sourceUrl', 'sourceLabel', 'inReplyToTweetId', 'inReplyToUser', 'mentionedUsers', 'coordinates', 'place', 'hashtags', 'cashtags', 'char_cnt', 'word_cnt', 'sentence_cnt', 'avg_word_size', 'avg_char_per_sent', 'avg_word_per_sent', 'stop_cnt', 'avg_stop_per_sent', 'avg_stop_per_word.

Diagram 2. Scraped Tweet's Attributes.

E. Process Framework

The Framework can be divided into the overall process workflow and the transformer classifier process. Tweets data scraped was first cleaned with the regex python library method by removing all the unnecessary links, hashtags, usernames, punctuation, and others. We dropped the duplicate tweets, preprocessed the text data with Natural Language Toolkit (NLTK) library, removed stop words, and then extracted related topics and topic models from the text data using Latent Dirichlet Allocation, as seen in Fig. 1.

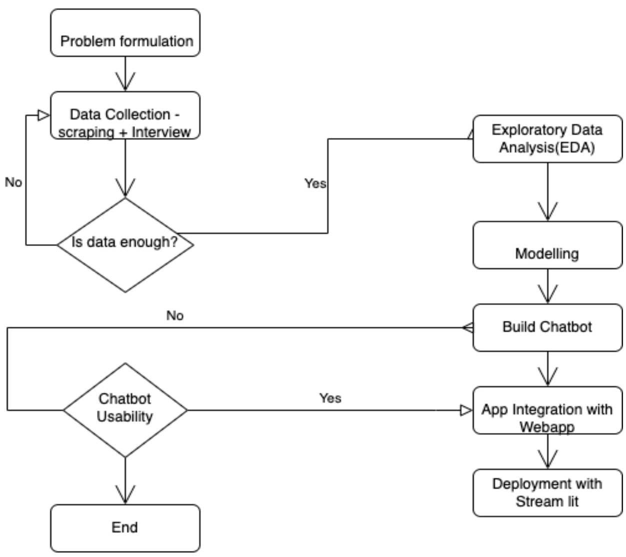

Fig. 1. Process workflow.

On the other hand, Fig. 2 prepared the classifier data using a hugging face transformer, a pre-trained model from the BERT framework, classify sentiments into positive and negative, which classifies the classifier data into 96% negative and 4% positive with the keywords: Panic; Anger;

Sad; Happy; Brave which was later used for training our chatbot using RASA, contained with Docker and deployed on the web app with Streamlit as shown in Fig. 2.

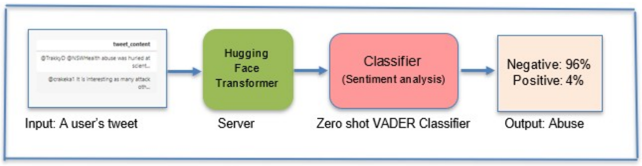

Fig. 2. Sentiment classifier with hugging face transformer.

V. Results

This section was structured into Exploratory Data Analysis, Topic Models generated, the chatbot designs, evaluation and finally, the usability of the Chatbot.

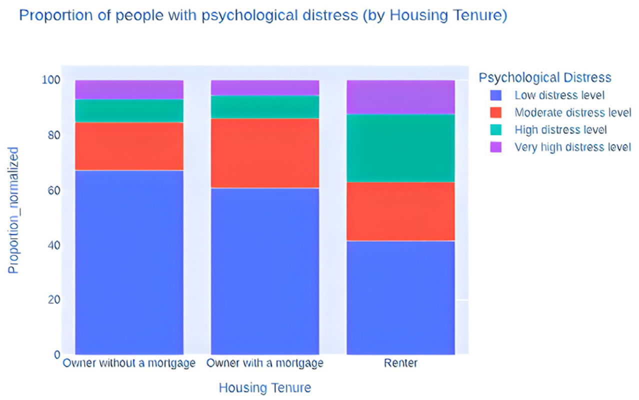

Fig. 3. Australians' proportion with psychological distress by housing tenures.

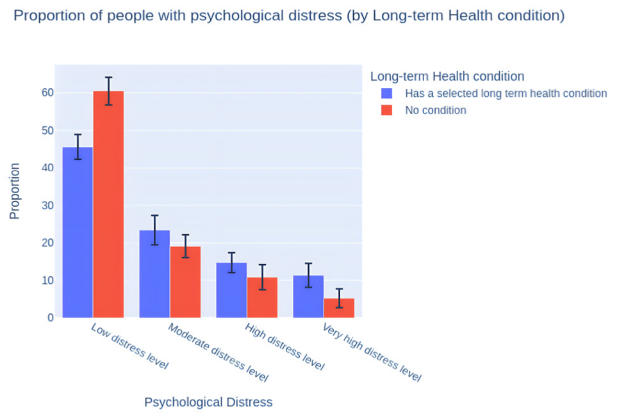

Fig. 4. Australians' proportion with psychological distress by long-term health condition.

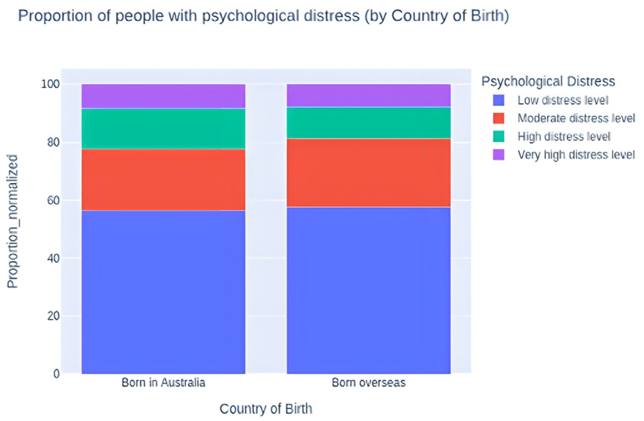

Fig. 5. Australians' proportion with psychological distress by Birth country.

A. Exploratory Data Analysis (EDA)

The EDA displayed justifiable reasons behind Australians' psychological distress. For example, Fig. 3 shows that Australians with rented apartments have a higher distress level than house owners with or without mortgages. Fig. 4 featured Australians with long-term health conditions who suffered emotionally.

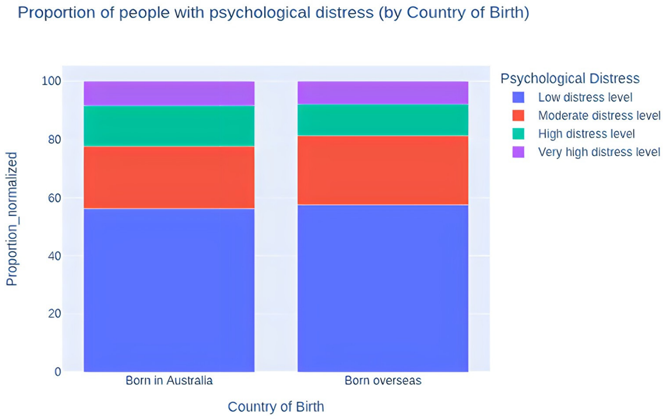

Fig. 6. Australians' proportion with psychological distress by Age group.

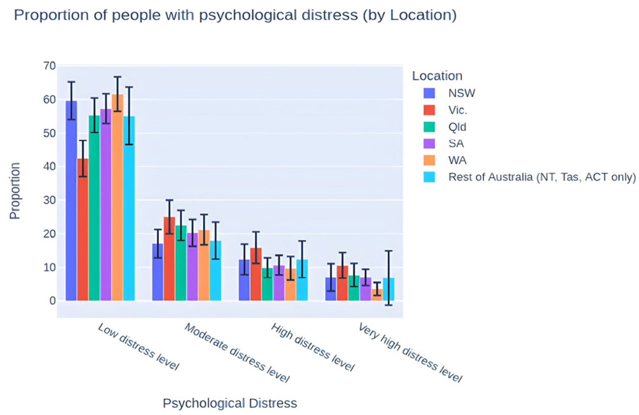

Fig. 7. Australians' psychological stress by location.

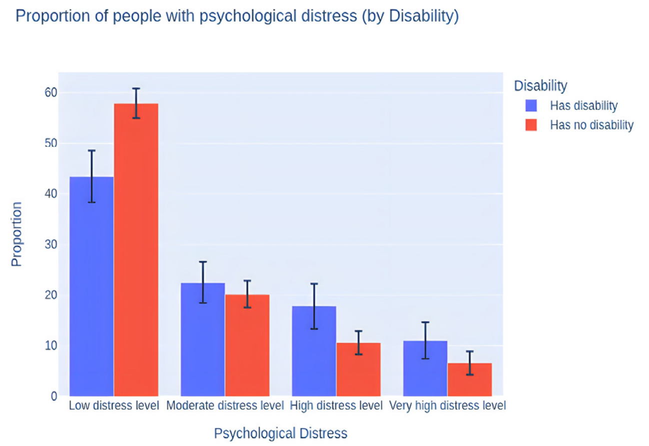

Fig. 8. Australians' psychological distress by disability.

The difference between Australian descent and non-Australians slightly affects their mental breakdown, as seen in Fig. 5. Distress levels of Australians by age group, as exhibited in Fig. 6, 18-34, are mentally distressed compared to 35-64 and 64 rarely suffer emotional trauma. This shows that People in Victoria are very distressed than New South Wales, Queensland, South Australia, West Australia, and the rest of Australia, as displayed in Fig. 7. Again, disabled

Australians are highly distressed than the ones without disabilities, as seen in Fig. 8. Also, Lone Australians and without children are equally distressed than the ones with Children as featured in Fig. 9.

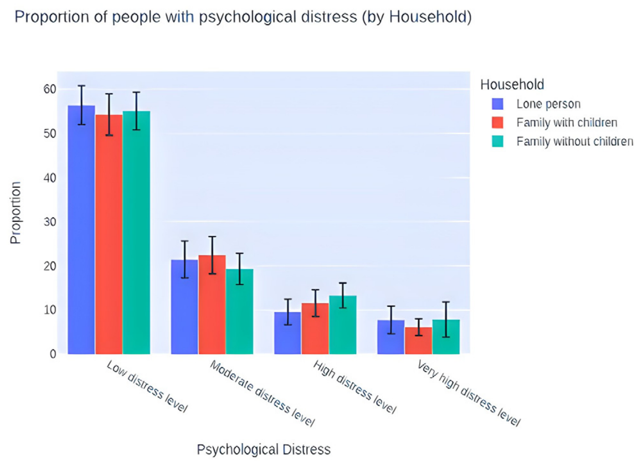

Fig. 9. Australians' psychological stress by household type.

B. *Topic Modelling*

This section discussed the top related topics generated from the N-gram ranking to the non-stopwords.

1) *Top Non-Stopwords:* The Top non-stop words featured in Fig. 10 are Covid, people, lockdown, coronavirus, and health, even when different contextual keywords were used to scrape Twitter, which proves that people mainly were sharing about the pandemic.

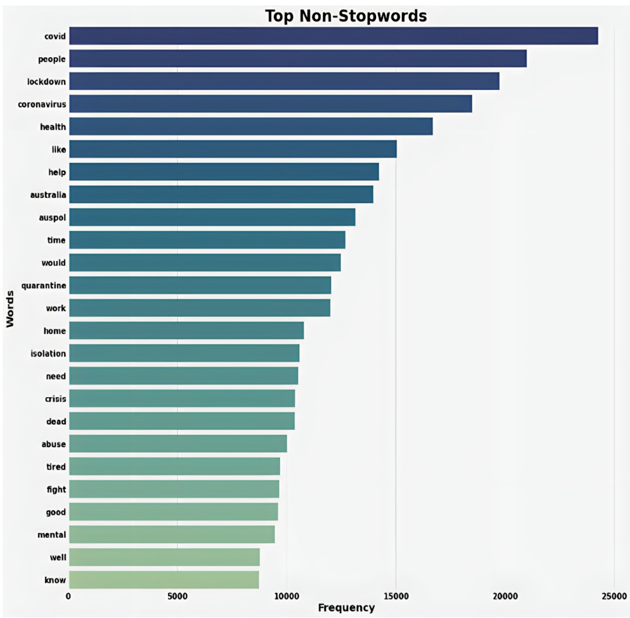

Fig. 10. Top non-stopwords.

C. *N-gram Ranking*

Top Bi & Tri-Grams: Most used bi-gram words shown in Fig. 11 are mental health, hotel quarantine, work home etc, and the Trigrams are Victoria Australia co, New South Wales, positive mental health mindset as shown in Fig. 12. This showed the impact of new rules and regulations in some part of Australia and the specific areas it affected during the pandemic.

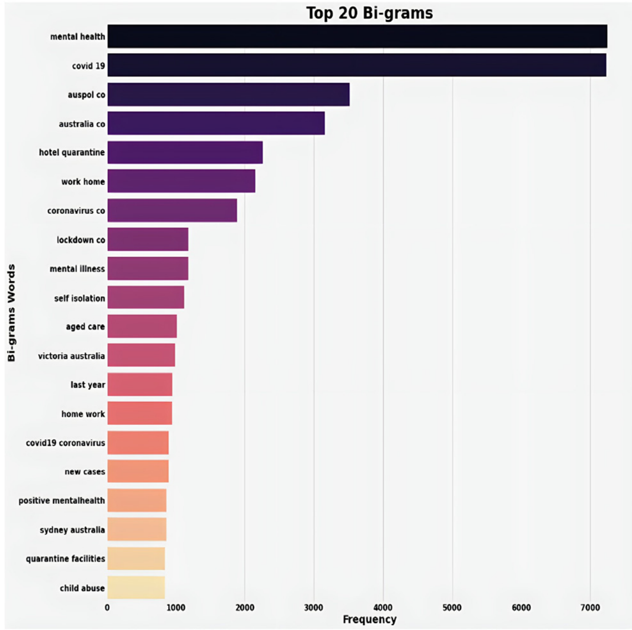

Fig. 11. Top 20 bi-grams non-stop words.

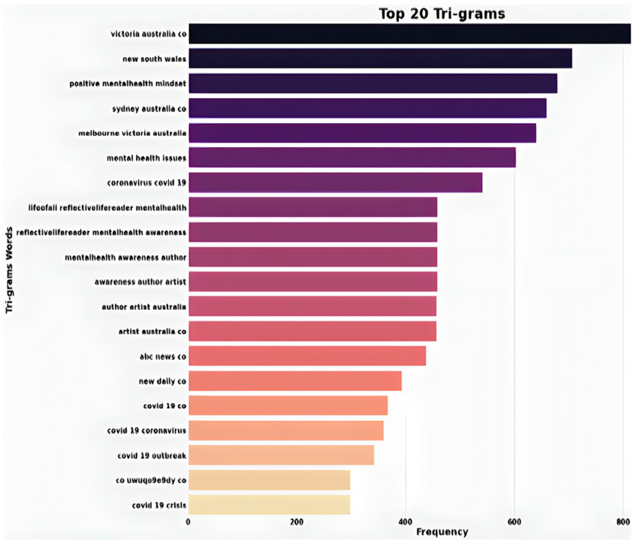

Fig. 12. Top 20 tri-gram non-stop words

VI. Implementation of JoyBot Chatbot

A. *Chatbot Design*

JoyBot chatbot was developed using the RASA (Receive, Appreciate, Summarize, Ask) Framework and Natural Language Processing. The Chatbot is composed of some specific terms:

1) *Intents:* These represent intentions the user wants to express when he submits his message to the Chatbot. Inside the intents, we provide some phrases the user may ask and responses that the Chatbot must use to answer the user. It's the work of the Developer here.
2) *Entities:* Entities are keywords that represent specific dates that the Chatbot may use to discuss with the user. Entities extract some values inside the user input (message). RASA works based on two python libraries, Rasa NLU and Rasa Core. The first one is Natural Language Understanding(NLU) which uses the intents to understand what the user wants and entities to extract some specific values to make the conversation more

interesting, then sends it to the RASA Core, which receives the data sent by Rasa NLU and processes it to find the correct answer, send the answer to the user as output, for having a response, it will look for the responses that the Developer provided to him inside the intents.

3) *Creating FAQs and Stories:* The initial step was to make FAQs, we used a one-intent FAQ and made numerous FAQs (faq/causes_mental_illness) in NLU.yml with answers in domain.yml (utter_faq/causes_mental_illness). For creating the conversation, we used stories.yml, as seen in Fig. 13, where we defined different approaches possible by the user. This functionality includes various options, buttons, replies etc. As shown in Fig. 14. domain.yml file, the process framework lists all intents, the bot's responses with their text, and the actions the bot can perform. The intents are used to train the NLU model. Note that any action or response we define has to be listed in the domain.yml like "JoyBot emergency", "help me", "code red", etc. We finally, used rule.yml to define the functionality (whenever the user calls faq, the bot must perform utter_faq).

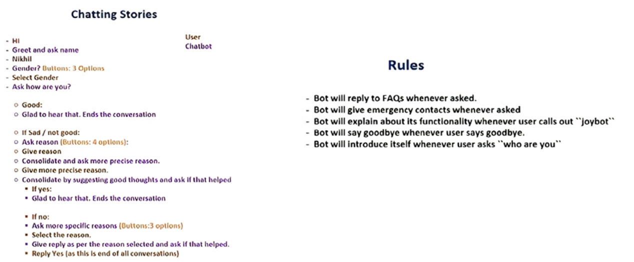

Fig. 13. Chatting stories.

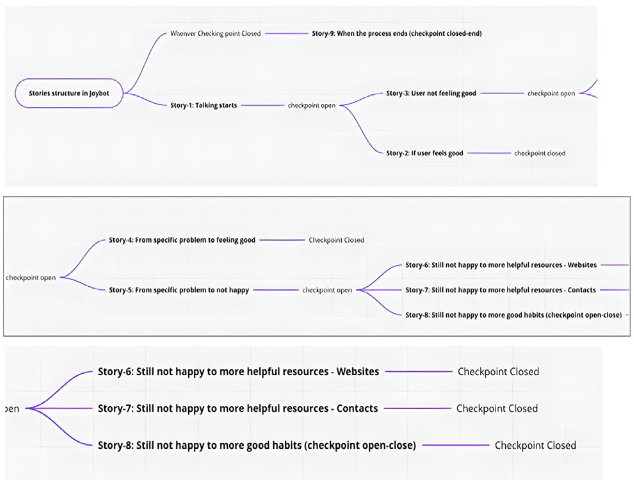

Fig. 14. Process framework of JoyBot.

B. Chatbot Containerization

The containerization for reuse is by creating the Dockerfile; Build the docker image; Push the image to the docker hub named; Deploy the application to an Azure virtual machine; Test the application in azure in 2 methods using rasa shell (command line) and postman (as a REST API).

C. Chatbot Usability

The deployed interfaces in black and white background can be seen in Figs. 15 and 16 respectively.

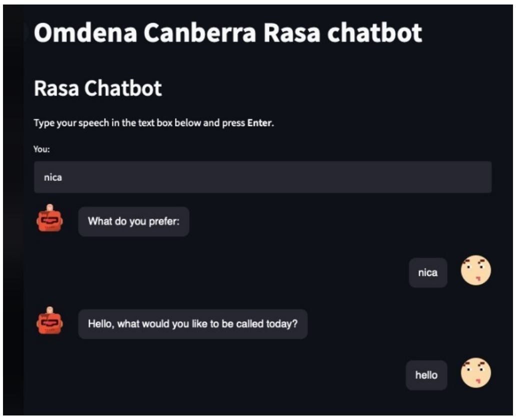

Fig. 15. Joybot interface I.

D. Chatbot Evaluation

We evaluate the chatbot using Intent Prediction Confidence Distribution as displayed in Fig. 17. The Intent prediction confidence distribution histogram visualizes the confidence in all forecasts, with green and red bars representing right and incorrect predictions, respectively. As shown in Fig. 17, the chatbot predictions for all the conversations keyed were 100% correct.

Fig. 16. Joybot Interface II

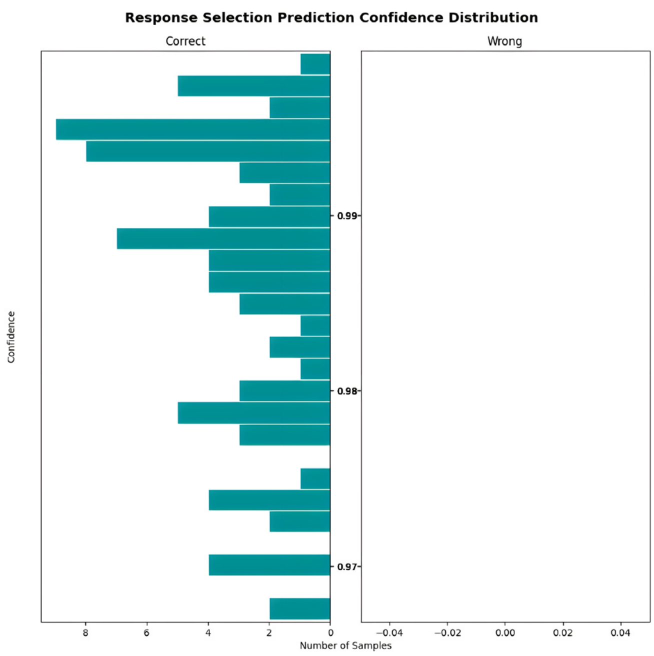

Fig. 17. Response selection prediction confidence distribution.

VII. Discussion

This project shows that Australians are psychologically distressed based on the following Factors: Long term health issues, Job Status, Housing, Location, and family type Disability thereby giving us a lead to training the data based on these pointers.

In conclusion, the R01 to RO5 objectives were met, which are to identify and discuss how mental health can be assisted with chatbot projects in Australia (RO1) by the first meeting and the background study of the project, according to RO2, which is to examine the level of health challenges in Australia (RO2), the EDA shows long term health condition can affect high psychological distress among Australians, speak with mental health professionals; and learn critical measures to preserving overall well-being(RO3) by interviewing mental health professional as a key informant and this was an eye- opener to how mental health can be discovered and managed, create a prototype chatbot or web tool to assist people in sticking to a healthy routine(RO4) by building a JoyBot using RASA framework using Streamlit. We tested the prototype to see how it affects the user's experience (RO5) with Intent Prediction Confidence Distribution and Response selection prediction confidence distribution.

VIII. Conclusion

In conclusion, JoyBot would serve as an effective, handy tool for Australians when deployed as a text message, guide them through Frequent Answering Questions (FAQ) and serve as a directory to the appropriate Psychologist at every instance, thereby reducing the overall workload on the Mental health sector in Australia.

Conflict of Interest

All authors of this manuscript are Freelance Machine Learning Engineers of the OMDENA-Australia Chapter. The authors have no other relevant affiliations or financial involvement with any organisation or entity with a financial interest in or conflict with the subject matter or materials discussed in the manuscript apart from those disclosed.

Author Contributions

Mary Adewunmi proposed the idea of a research paper and wrote the manuscript; Tanya Dixit brought the problem statement; Adish Ashraff managed the project; Nilkhi Shrestha designed the framework and chatbot; Veronica Gail Medrano and Bhushan Chougule curated the data; Ahmed Fahim deployed the project on docker; Navaneeth Tirupathi and Sudha Sushma analysed the data; all authors had approved the final version.

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