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Rule-Based Chatbot for Early Self-Depression Indication: A Promising Approach

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***Abstract*—Depression is a prevalent mental health condition worldwide, often characterized by persistent sadness, loss of interest or pleasure, and feelings of worthlessness. Depression is the leading cause of mental health issues worldwide, and it is becoming more severe without self-awareness, early screening, and further medication. Early detection and intervention are critical in mitigating its adverse effects. Leveraging advancements in Artificial Intelligence (AI), particularly in Natural Language Processing (NLP), chatbots have emerged as potential tools for early depression indication. Chatbots are beneficial tools in the mental health domain, such as in assisting mental health risk users. This paper presents the development of a rule-based chatbot aimed at detecting early signs of depression through conversational interactions by screening symptoms of depression. Predefined rules are developed to ensure the assessment can generate reliable results. The rule-based chatbot is developed to assist in depression indication assessment for mental health-risk individuals at an early stage and provide the risky patient with appropriate support and resources. The chatbot assessment has adopted the Depression Anxiety and Stress Scale 21 (DASS21) instrument. Based on the System Usability Scale (SUS) results, the rule-based chatbot has been accepted by all 30 respondents with good acceptance of an average SUS score of 77.2. Thus, the outcome of this chatbot can be utilized as a professional platform to encourage self-disclosure of mental depression indications for users, and it can be beneficial as the initial reference before recommending further action before the earlier help-seeking.**

***Keywords*—Depression; chatbot; early indication; rule-based chatbot; predefined rules; self-depression indication.**

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I. INTRODUCTION

Depression is the primary cause of poor health and disability worldwide. As per the most current evaluations from the World Health Organization (WHO), approximately 280 million individuals are presently living with depression [1]. The crisis of mental health is expected to be the second highest in Malaysia. The study conducted by the Ministry of Health Malaysia revealed that every ten adults aged 16 years old and above suffer from some form of mental illness [2]. The suicide rates increased significantly for males between 2014 and 2019 [3].

Depression can be the cause of loss of job and unemployment [4] [5], job stress, workload, burnout [6] [7] [8], unstable finances [9], and family problems [10]. In addition, recent statistics on the factors affecting work-related depression, anxiety, and stress among fresh graduates in Malaysia caused remarkably by job demand or workload (73.6%), working hours (36.4%), working environment (36.4%), salary (28.1%), and coronavirus disease 2019 (COVID-19) pandemic (27.3%). Moreover, other reasons (10.8%) include health, job performance, interpersonal relationships, and intrapersonal issues [11]. The COVID-19 pandemic and the Movement Control Order (MCO) around the globe have impacted most non-essential services; they cannot be operated as usual. Consequently, many people have lost their jobs and been in financial crises. In addition, the COVID-19 pandemic has had a significant impact on mental health [12].

Digital Mental Health Intervention (DMHI) is an initiative that raises awareness of mental health issues. From the perspective of mental healthcare professionals, the chatbot can help support people with mental health issues [13]. The researcher reported that the chatbot's acceptability is rated as high in the mental health domain [14]. DMHI is promising in addressing gaps in mental health service provision.

However, DMHI drawbacks have been reported, such as the existing application's lack of scientific evidence about its efficacy, pending replication, inability to understand the content and context of users' input correctly, and the Artificial

Intelligence (AI) chatbot's inability to generate a relevant response. Progressive and advanced technology like chatbots has increased in many domains, moving from traditional to digital platforms to assist users.

Chatbot is an automated program designed to interact with users in a human-like manner. It typically requires minimal or no cost to use. It can be available at any time of day or week, regardless of time or physical location. This makes it an attractive solution for many fields and domains needing more staff or financial resources to maintain 24/7 human support. The most commonly cited motivational factor is productivity, with the chatbot providing timely and efficient help or information [15].

The use of chatbots in the healthcare sector has grown, with these systems designed to deliver customized health and therapy information, provide patient-related products and services, and offer diagnoses and treatment recommendations [16]. Chatbot can care for the user's emotional health [17] [19]. In addition, the chatbot also can remind patients to take their pills [18]. Thus, the chatbot has the potential to be used to assist users having mental health issues [14], [19], but not to replace mental health professionals. In this study, we focused on the benefits of a rule-based chatbot for indicating depression in individuals as early as possible.

This paper is structured as follows: Section 2 reviews the material used to indicate depression and chatbot potential for mental health and highlights the research methodology phases. Section 3 discusses the outcomes of the rule-based chatbot in assisting people at risk. Lastly, Section 4 concludes the benefits of a rule-based chatbot for early self-depression indication.

II. Material and Method

A. Mental Health Issues and Scenario

Depressive disorder, also known as depression, is a common mental disorder; it can happen to anyone. Depression is one of the mental illness issues that could influence how people think, feel, and behave. It is related to someone who has unstable emotions such as sadness for a prologue period, and it can disturb routine daily. The mental health issue has garnered more attention recently, particularly to the riskiest people who are living a challenging life after the coronavirus disease 2019 (COVID-19) pandemic.

The issue of mental health, such as mental illness, can be categorized into a few groups, such as schizophrenia, mood disorder, bipolar disorder, and depression [2]. Depression can be categorized into levels such as everyday, mild, moderate, severe, and extremely severe. Worse scenario, it can lead to suicide attempts if there is no solution to control depression. Ministry of Health Malaysia has recorded 1,080 suicide attempt cases between January and December 2020 [20]. The findings surprisingly showed how severe depression is among Malaysians.

Research claims that women tend to have depression rather than men due to biological factors and exposure to women to depression [21]. Depression is affected differently for both; women express internal symptoms while men express external symptoms. A study of dizygotic twins found that women were more sensitive to interpersonal relationships, while men were more responsive to external career and goal-oriented factors. Besides, women may experience specific forms of depression-related conditions, including premenstrual dysphoric disorder, postpartum depression, and postmenopausal depression and anxiety [22].

B. The Instrument Tools to Indicate the Prevalence of Depression

The presence of depression can be detected using the existing instrument tool in mental health. The existing instrument tool consists of a set of questionnaires such as the Malay Depression Anxiety Stress Scale (DASS21) [23], [24] [25], [26], Maslach Burnout Inventory [27], Patient Health Question 9 (PHQ-9) [28], [29], [30], Beck Depression Inventory (BDI) [23], [25], [31], WHOQOL-BREF [32], [33], [34], Whooley Question [35], General Health Question (GHQ-12) [36], and Administrative Stress Index (ASI) [26].

However, not all instrument tools are applicable for users of all ages and are relevant for specific conditions. Recent studies found that PHQ-9 does not give an accurate result to estimate due to the overestimated prevalence of depression [35]. In contrast, PHQ-9 is widely validated, but it was recommended to have two stages of screening [29]. There was a suggestion that mental health professionals share their opinions in supporting mental health issues.

Based on surveys conducted from 2010 to 2021, DASS21 was the popular instrument used among Malaysians. DASS21 has three components: depression, anxiety, and stress. It is reliable and valid for Malaysians because it provided robust data based on the largest sample size for construct validity [37]. However, the instruments were used for different purposes. Recent studies claim that the combination of the instruments was used to detect depression [23] [25]. For example, a combination of instruments such as DASS21, Hospital Anxiety and Depression Scale (HADS), and GHQ-12 was used to assess users' experiences of anxiety to achieve accurate results.

Technology intervention is growing in the mental health domain. DMHI's focus on depression was reported in literature reviews such as mobile apps [38] [39] [40], web-based [41] [42] [43], telemedicine [44] [45], and AI chatbot [46]. However, there are drawbacks found in the previous work, whereas DMHI is not applicable for all users due to choppy movement and delay in audio [45]; in telemedicine, some adolescents felt using the web-based system did not help them and required some time for loading [47]; most of the currently available apps lack scientific evidence regarding their efficacy, including pending replication studies [48]; and without the capability to accurately grasp the content and context of a user's input, a chatbot cannot produce a relevant response [49].

In addition, the counseling unit within the organization has a web-based system to communicate with people in need. For example, counselors at public universities can do depression assessments by completing the assessment tool. For instance, Universiti Putra Malaysia (UPM) provides assessment screening questionnaires based on a mental healthcare instrument called DASS21 [50]. The result will be displayed after the user has entered all the compulsory information, such as demographic and contact information. The counselor will contact the user for an appointment if necessary. The user must bring a hard copy of the assessment result during the appointment session.

Besides, private psychiatric companies also use web-based systems to provide depression assessments. The user must enter all compulsory demographic information such as gender, race, education level, age, marital status, and occupation before assessment. The web-based system then generates the result once the evaluation is completed. This web-based system provides general information such as when to see a doctor, the signs of depression, general information about anxiety, the hospital, and the contact number to make the appointment at a private clinic. However, the system is less interactive, and some information needs to be updated.

Web interactivity is the interactive feature embedded in a website that offers information exchange between the user and the web. It is one of the essential elements to create a good experience for users and attract them to use the system. In some studies, chatbot-based assessments that use rule-based techniques could provide highly engaging, create bonding between chatbot and user, and effectively collect anonymized mental health data among employees [51].

Once the assessment is completed, participants will receive their results and recommendations. For example, an overall report will be presented to the company to assess the level of mental health conditions among their employees. Thus, the company could offer valuable insight and recommend further campaigns to increase awareness about mental health conditions. This has been seen as an approach to improve mental health issues [52].

C. Chatbot to Benefit Mental Health Domain

A chatbot is a computer program designed to interact with human users through spoken, written, or visual language. Chatbot can benefit users such as 24/7 availability, automation of operations, reduction of human errors, learning and updating, management of multiple users, and customer support; it is being utilized in a variety of domains, including business, customer services, education, healthcare, mental health, and others.

Chatbot has the potential to be helpful in the treatment of mental disorders, particularly for those who are unwilling to seek mental health advice for fear of discrimination or negative perceptions of those who see them as having mental health issues [52]. Chatbot evaluation needs to be addressed in the literature [53] and assessing and comparing different chatbot systems in terms of effectiveness, efficiency, and user satisfaction is challenging. Most researchers reported that the usability evaluation concentrates on user satisfaction [54], [55], [56].

Digital mental healthcare has the potential to bring more access, especially to mental healthcare provision [57]. Online survey results indicated that over half of the participants believe chatbots can support mental health from a professional perspective and that there are benefits associated with mental healthcare chatbots [58]. Moreover, chatbots can act as intermediaries, encouraging individuals to engage in deeper self-disclosure with an actual mental health professional [59]. There are two types of chatbots: rule-based chatbots and AI chatbots. Rule-based chatbots, or decision-tree bots, use a series of defined rules.

A rule-based chatbot classifies the text and generates an appropriate response for the user by using pattern-matching [60]. The user inputs a sentence (stimulus) and generates the corresponding output (response). Consequently, it will use the pattern-matching algorithm to compare user input to a rule pattern and select a predefined reaction from a set of responses. Artificial Intelligence Markup Language (AIML), Chat script, and River script are the most popular languages for implementing chatbots with a pattern-matching approach [60].

An AI chatbot employs machine learning technology to comprehend the context and intent behind a question before crafting a response. AI is increasingly becoming part of our daily lives by developing and using intelligent software and hardware, known as intelligent agents or chatbots [60]. It is a computer application programmed to learn and form replies based on the previous data from the user. The earlier data collection will be a knowledge for the chatbot to respond to the user, which can be collected by training the chatbot. Without proper training, a chatbot is forced to be shut down because it can cause people to interact with the bot inappropriately, using offensive language and content [61].

A chatbot is created for a particular purpose. How it operates depends on the chatbot type, either a rule-based chatbot or an AI chatbot. A rule-based chatbot can only comprehend the limited set of options it has been taught. The predefined rules govern chatbot conversation. A rule-based chatbot is typically simpler to develop, using a simple true-false algorithm to comprehend user queries and provide pertinent responses.

On the other hand, the AI chatbot is equipped with a synthetic brain. It has been trained using a machine learning algorithm and can comprehend free-form queries. Not only does it comprehend commands, but it also comprehends the language of nature. As the chatbot gains knowledge from interacting with users, it continues to advance. The AI chatbot recognizes the user's language, context, and intent and responds accordingly.

Chatbots can range from basic programs that provide single-line answers to more advanced digital assistants that learn and adapt to offer increasingly personalized responses based on the information they collect. As the use of chatbots continues to grow across various fields and domains, developers are prompted to create these systems within tight timeframes and with limited initial knowledge.

Consequently, there is a high probability that the chatbot will fail. The researcher conducted a short survey about the failure to raise the state-of-the-art chatbot. The result showed a need to realize how chatbots are currently being used and designed and their primary sources [62]. Thus, the development of chatbots requires in-depth knowledge of the user's motivation for using the technology, which allows the practitioner to overcome challenges regarding adopting the technology [63].

Moreover, general knowledge is needed to understand the relationship between humans and chatbots. Therefore, practitioners should have knowledge and clarity about state-of-the-art chatbots to minimize failure and facilitate better human-chatbot interaction experiences in the future [15]. The state-of-the-art refers to the fundamental concept of a chatbot and the design technique applicable to it, such as the classification of a chatbot, components of the chatbot, and technique used by the chatbot [64]. More attention is needed to evaluate chatbots to prevent them from harming users. Usability is one of the key areas in software quality, and evaluation is needed to ensure that chatbots achieve effectiveness, efficiency, and satisfaction according to the ISO 9241-11 standard.

D. Research Processes and Activities

Research methodology describes the research processes and activities following four main phases, as depicted in Fig. 1.

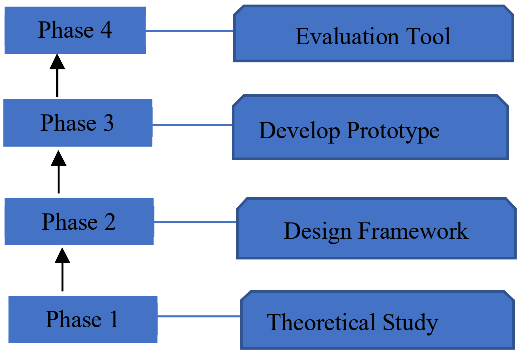


Fig 1: Research Methodology Phases

The first phase of the research process is theoretical study, which identifies the layout of the chatbot, how it will be implemented, the technology behind the chatbot, and a similar prototype. This research used a multi-method approach to collect primary and secondary data. A systematic literature review of the existing literature related to using chatbots in the mental health domain as the chatbot is a promising technology for facilitating mental health assessment. The sources of previous work related to the rule-based techniques are being analyzed to ensure the chosen method is applied to this study.

The diversity of scientific databases such as Google Scholar, Science Direct, ACM Database, IEEE Xplore, and Semantic Scholar are being referred to. A backward and forward reference list check was performed for the included studies and relevant reviews. Specific keywords guided study selection and data extraction. The extracted data were synthesized using a narrative approach. Chatbots were categorized based on their purpose, platform, response generation method, dialog management component, and their benefits in the mental health domain.

Besides, semi-structured interviews were conducted with SMEs, psychiatrists, and registered counselors in public universities. The respondents have more than five years of experience in mental health. The list of topics and structure of questions were designed to address how DGHI assists in the earlier detection of mental health issues, the appropriate use of instrument tools, and the promise of chatbots in the mental health domain. So, the SMEs were interviewed to collect information about mental health concerns, including the appropriate instrument to detect depression in the workplace. Incorporating relevant instruments for depression in technology could benefit users.

The second phase, the chatbot's design, uses a conceptual diagram to identify the components included during its development. The conceptual diagram in Fig. 2 depicts the relationship among the chatbot's components. It displays a three-tier structure comprising the presentation, application, and back-end tiers.

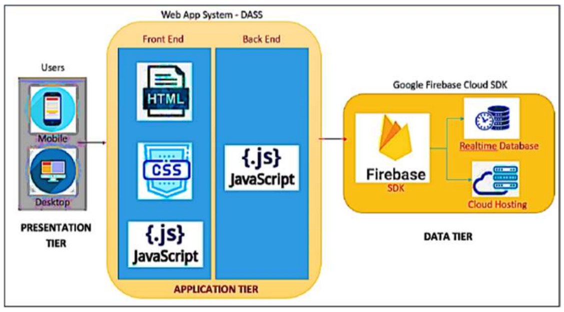


Fig. 2 Conceptual diagram of the chatbot development

The presentation tier is the user interface, allowing the interaction between the user and the application. It can be presented using a web browser as a desktop or mobile phone. The user can assess the chatbot using any supported mobile, desktop, or iPad device. The application tier, also known as the logic tier, is the heart of the application. The application is developed using programming languages such as Hyper Text Markup Language (HTML), Cascading Style Sheet (CSS), JavaScript as a front-end, and JavaScript as a back end.

The Data tier store is where the information processed by the application is stored and managed. This chatbot uses Firebase as a Backend-as-a-Service (BaaS). BaaS is a cloud service model that allows developers to outsource all the behind-the-scenes aspects of the application, focusing on writing and maintaining the front end. Thus, Firebase is selected because it is a real-time database, and cloud hosting allows secure access directly to the database from client-side code.

In the third phase, a few steps need to be considered to develop a chatbot, such as defining its purpose, understanding the audience, determining the chatbot personality, designing the user journey and conversation, developing the chatbot, integrating with NLP, and testing. The prototype of this chatbot uses the rule-based technique, as it provides a consistent response based on the predefined rules and ensures the user receives the same level of assessment.

In the fourth phase, the chatbot's usability was assessed using the SUS method. The SUS has been a reliable and validated tool for over 30 years, and it is widely used to evaluate various systems. In addition, SUS provides a quick, effective, and reliable method for assessing perceived ease of use. It can assist practitioners in identifying potential issues with a design solution and is a highly robust and versatile tool for evaluating usability.

III. Results and Discussion

A. The Development of a Rule-based Chatbot for Self-Depression Screening

Rule-based techniques can solve the issue of irrelevant results as the chatbot responds appropriately because it is based on the rule classifier and the selection of answers from users' choices. The input from users can be collected and become knowledge-based so the chatbot can give a response. The development of the rule-based chatbot for early depression indication involved several vital steps. First, a comprehensive set of rules was established based on established criteria for assessing depression, including symptoms, severity, and risk factors. These rules encompassed linguistic cues, such as specific keywords and phrases indicative of depressive thoughts and emotions, and behavioral patterns, such as social withdrawal, breathing difficulties, and fast heartbeat. Next, the chatbot's conversational flow was designed to elicit relevant information from users while providing empathetic responses and psychoeducation on depression. Finally, the chatbot was implemented and tested on diverse users to evaluate its accuracy and usability.

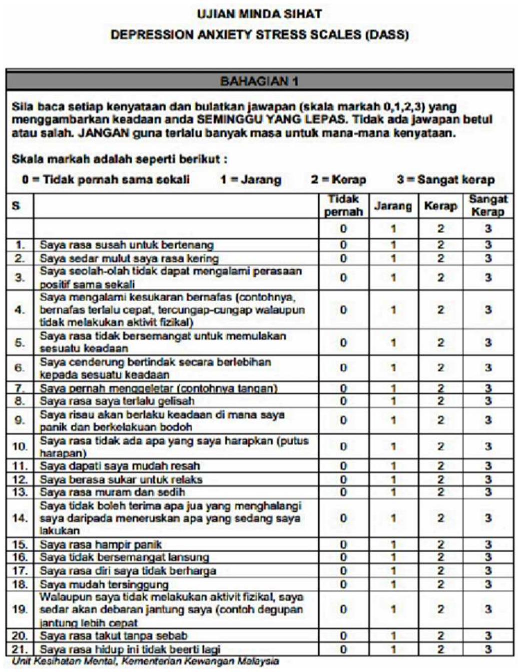
The user interface (UI) is a medium for users to interact with the chatbot. The chatbot UI is developed using programming languages such as HTML, CSS, and JavaScript. The UI can be accessed via desktop and mobile using any browser. The Home page describes the system's functions, how to use it, and the module it provides. To evaluate its effectiveness, a rule-based chatbot depression instrument tool, DepBot, was developed. DepBot is meant to assist depression risk users in indicating their depression status at an early stage by doing a self-depression indication assessment. The welcome page collects users' demographic data, as shown in Fig. 3.

Fig. 3 Main page of the depression instrument tool

The UI controller directs the user’s request to the message analysis component, which determines the user’s intent and extracts entities based on pattern matching. As shown in Fig. 4, the Depression Instrument Tool page will be displayed after the user clicks Ujian Saringan Kesihatan Minda.

Fig.4 The User Message Analysis Component

The user must complete all twenty-one questions, and the result will be calculated according to the specific calculation. The assessment was conducted using the existing instrument tool, namely DASS21 questionnaires for mental health. The main feature of the proposed chatbot is the assessment for depression indication. We used the Malay language mainly to raise a better understanding of the context, meaning, and content of our targeted Malaysian respondents, as shown in Fig. 5.


UJIAN MINDA SIHAT

DEPRESSION ANXIETY STRESS SCALES (DASS)

BAHAGIAN 1

Sila baca setiap kenyataan dan bulatkan jawapan (skala markah 0,1,2,3) yang menggambarkan keadaan anda SEMINGGU YANG LEPAS. Tidak ada jawapan betul atau salah. JANGAN guna terlalu banyak masa untuk mana-mana kenyataan.

Skala markah adalah seperti berikut :

0 = Tidak pernah sama sekali 1 = Jarang 2 = Korap 3 = Sangat kerap

S		Tidak pernah	Jarang	Kerap	Sangat Kerap
		0	1	2	3
1.	Saya rasa susah untuk bertenang	0	1	2	3
2.	Saya sedar mulut saya rasa kering	0	1	2	3
3.	Saya seolah-olah tidak dapat mengalami perasaan positif sama sekali	0	1	2	3
4.	Saya mengalami kesukaran bernafas (contohnya, bernafas terlalu cepat, tercungap-cungap walaupun tidak melakukan aktivit fizikal)	0	1	2	3
5.	Saya rasa tidak bersemangat untuk memulakan sesuatu keadaan	0	1	2	3
6.	Saya cenderung bertindak secara berlebihan kepada sesuatu keadaan	0	1	2	3
7.	Saya pernah menggeletar (contohnya tangan)	0	1	2	3
8.	Saya rasa saya terlalu gelisah	0	1	2	3
9.	Saya risau akan berlaku keadaan di mana saya panik dan berkelakuan bodoh	0	1	2	3
10.	Saya rasa tidak ada apa yang saya harapkan (putus harapan)	0	1	2	3
11.	Saya dapati saya mudah resah	0	1	2	3
12.	Saya berasa sukar untuk relaks	0	1	2	3
13.	Saya rasa muram dan sedih	0	1	2	3
14.	Saya tidak boleh terima apa jua yang menghalangi saya daripada meneruskan apa yang sedang saya lakukan	0	1	2	3
15.	Saya rasa hampir panik	0	1	2	3
16.	Saya tidak bersemangat lansung	0	1	2	3
17.	Saya rasa diri saya tidak berharga	0	1	2	3
18.	Saya mudah tersinggung	0	1	2	3
19.	Walaupun saya tidak melakukan aktivit fizikal, saya sedar akan debaran jantung saya (contoh degupan jantung lebih cepat	0	1	2	3
20.	Saya rasa takut tanpa sebab	0	1	2	3
21.	Saya rasa hidup ini tidak beerti lagi	0	1	2	3

Unit Kesihatan Mental, Kementerian Kewangan Malaysia

Fig. 5 DASS21 Instrument Tool for Depression in Malay Language

The set of questionnaires consists of twenty-one (21) questions, divided equally into three categories: stress, anxiety, and depression. Each category holds seven questions, as shown in Table 1.

TABLE I

DASS21 ASSESSMENT CLASSIFICATION

Category	Question Number						
Stress	1	6	8	11	12	14	18
Anxiety	2	4	7	9	15	19	20
Depression	3	5	10	13	16	17	21

Four (4) options for the answer were given, and the options were categorized based on the symptom level. The first option is *Tidak Langsung* (None) holds the value of zero (0); the second option is *Sedikit/Jarang-Jarang* (Little/Rarely) holds the value of one (1); the third option is *Banyak/Kerapkali* (A Lot/Often) holds the value of two (2); last option is *Sangat Banyak/Sangat Kerap* (Very Much/Very Often) holds the value of three (3). The predefined rules, such as If Else, have been created to generate the result. The user needs to select one answer from 0 to 3, but if the user entered it differently, the chatbot will ask to re-enter from the answer selection.

The user is required to select one option given for each of the questions. It consists of error handling; the user will be reminded to enter the proper selection of answers if the chatbot received the wrong value as an option from users. The total value from all the questions will be multiplied (*) by two (2). The total score will be mapped into scores from the severity level of depression, such as normal, mild, moderate, severe, and extremely severe. Fig. 6 indicates the rule classifier used to calculate the user's score.

```
For (var i=0;i<userSetAnswers.length;i++)
{
 //Assessment Score
 If(userSetAnswers[i].rank == 1 || userSetAnswers[i].rank
==6 || userSetAnswers[i].rank ==8 ||
userSetAnswers[i].rank ==11 || userSetAnswers[i].rank ==
12 || userSetAnswers[i].ranl ==14 ||
userSetAnswers[i].rank == 18)
stressScore = stressScore + userSetAnswers[i].answer;
userSetAnswers[i].rank == 19 \\ userSetAnswers[i].rank
==20)
anxietyScore = anxietyScore +  userSetAnswers[i].answer;
```

Fig.6 Rule Classifier in Chatbot

The depression Assessment Result page will be displayed after the user has completed the assessment, as shown in Fig. 7. The total score from each category needs to be multiplied by 2, and the result will be mapped to the score level of severity shown in Table 3. For example, if the user selects number 2 for each of the questions under the depression category, then the total score is 14. Then, the total score will be multiplied by two (2) to get the overall result.

Fig. 7 Result of the depression assessment

The overall result will be mapped into scoring in Table 2, and the user will get a moderate result for depression. The concept of calculation is the same for the other question categories. The result shows that those with moderate and above will be recommended to see the counselor by booking the appointment provided in this chatbot.

TABLE II
SEVERITY LEVEL OF DEPRESSION

Level of Severity	Depression	Anxiety	Stress
Normal	0-9	0-7	0-14
Mild	10-13	8-9	15-18
Moderate	14-20	10-14	19-25
Severe	21-27	15-19	26-33
Extremely Severe	28+	20+	34+

These modules are used in the chatbot since it can control and update the conversational context. The dialog management component typically includes the following modules such as ambiguity handling, data handling and error handling. However, this chatbot does not have ambiguity handling and data handling because it is specific to the close domain and depression assessment. Nevertheless, this chatbot is provided with error handling to cope with unexpected errors to ensure proper chatbot operation. For example, the user is required to select the given option for each of the questions. If the user enters other than the options, the chatbot will keep reminding the user to enter the correct answer as in (1).

(1)

```
}
else{
    pushMessage(message,2);
    document.getElementById("client-
response").value = "";
        pushMessage("Sila masukkan jawapan
    yang betul",1); pushMessage("0-Tidak
    Langsung | 1-Sedikit/Jarang-Jarang | 2-
    Banyak/Kerapkali | 3-Sangat Banyak/Sangat
    Kerap",1);
        pushMessage("Soalan"+questionnaireSets
    [qCount-1].rank + ":" +
    questionnaireSets[qCount-1].question,1);
    }
}
else{
    pushMessage(message,2);
    document.getElementById("client-
response").value = "";
        pushMessage("Sila masukkan jawapan
    yang betul",1); pushMessage("0-Tidak
    Langsung | 1-Sedikit/Jarang-Jarang | 2-
    Banyak/Kerapkali | 3-Sangat Banyak/Sangat
    Kerap",1);
        pushMessage("Soalan"+questionnaireSets
    [qCount-1].rank + ":" +
    questionnaireSets[qCount-1].question,1);
    }
}
```

The chatbot's backend is developed using JavaScript and integrated with Firebase. Firebase is Google-backed application development software that allows developers to build web applications. It offers tools for tracking analytics, reporting issues, fixing application crashes, and conducting product experiments.

The response generation component for this chatbot uses a rule-based approach. Rule-based selects responses from a set of rules without generating next-text responses. In this case, it required a source of data (instrument depression tool) and a set of rules to manipulate the data. Rules are sometimes called IF statements as they tend to follow the line of IF X happens THEN do Y, as in (2).

```
For(var i=0;i<userSetAnswers.length;i++)                    (2)
{
        //Assessment Score
        If(userSetAnswers[i].rank  ==  1  ||
userSetAnswers[i].rank      ==      6      ||
userSetAnswers[i].rank      ==      8      ||
userSetAnswers[i].rank      ==      11     ||
userSetAnswers[i].rank      ==      12     ||
userSetAnswers[i].rank      ==      14     ||
userSetAnswers[i].rank == 18)
stressScore       =       stressScore       +
userSetAnswer[i].answer;


        If(userSetAnswers[i].rank  ==  2  ||
userSetAnswers[i].rank      ==      4      ||
userSetAnswers[i].rank      ==      7      ||
userSetAnswers[i].rank      ==      9      ||
userSetAnswers[i].rank      ==      15     ||
userSetAnswers[i].rank      ==      19     ||
userSetAnswers[i].rank == 20)
anxietyScore       =       anxietyScore       +
userSetAnswer[i].answer;


        If(userSetAnswers[i].rank  ==  3  ||
userSetAnswers[i].rank      ==      5      ||
userSetAnswers[i].rank      ==      10     ||
userSetAnswers[i].rank      ==      13     ||
userSetAnswers[i].rank      ==      16     ||
userSetAnswers[i].rank      ==      17     ||
userSetAnswers[i].rank == 21)
depressionScore     =     depressionScore     +
userSetAnswer[i].answer;
}
```

B. *The Assessment for the Usability*

SUS consists of ten questions and is designed to get a response from the representative user quickly. Most researchers used SUS because of the *Response Generation Component*. The response generation part for this chatbot uses a rule-based approach. Rule-based selects responses from a set of rules without generating next-text responses. In this case, it requires a source of data (an instrument that can collect reliable feedback and repeat. SUS needs a minimum number of respondents to get reliable data. SUS will be calculated according to the value held by each Likert Scale, shown in Table 3.

TABLE III
POINT BREAKDOWN OF SUS [66]

Level of Likert Scale	Score
Strongly Disagree	1 point
Disagree	2 point
Neutral	3 point
Agree	4 point
Strongly Agree	5 point

The chatbot needs to be tested in terms of its usability to follow software quality, such as effectiveness, efficiency, and satisfaction. Therefore, the test case technique design is used for further enhancement to test the chatbot's functionality. Thirty respondents from various IT and non-IT backgrounds have experience in usability testing for the proposed depression indication rule-based chatbot. The majority of 73% are female and 27% are male. They have been categorized into age ranges, including 30% are 26-31 years old, 23% are 32-36 years old, 20% are 37-42 years old, 13% are 43-48 years old, 7% are 20-25 years old, and 7% are 49 years old and above. Regarding job positions, 53% were technical staff, 30% were supporting staff, and 17% professional staff. Job experience data showed 33% between 1-5 years, 27% between 6-11 years, 27% between 12-17 years, and 13% for 18% and above. The respondent's answer and the corresponding number score for each response are shown in Table 4.

TABLE IV
SUS SCORE FOR 30 RESPONDENTS

No of User	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Total Odd Number Question (-5)	Value X	Total Even Number Question	(25 -) Total Even Number	Value Y	Total Score (X+Y) * 2.5	New Value
1	4	3	5	2	5	1	5	5	5	1	24-5	19	12	25-12	13	32*2.5	80
2	3	4	3	1	3	1	4	4	5	1	18-5	13	11	25-11	14	27*2.5	68
3	4	4	5	1	5	1	5	4	5	1	24-5	19	11	25-11	14	33*2.5	83
4	4	4	3	1	4	1	3	4	3	1	18-5	13	11	25-11	14	27*2.5	68
5	5	4	5	1	5	1	5	3	5	1	25-5	20	10	25-10	15	35*2.5	88
6	3	3	4	1	4	2	4	4	4	2	19-5	14	12	25-12	13	27*2.5	68
7	4	4	4	2	4	1	5	3	4	1	21-5	16	11	25-11	14	30*2.5	75
8	5	5	5	1	5	1	5	5	5	1	25-5	20	13	25-13	12	32*2.5	80
9	4	4	4	1	5	1	5	5	5	1	23-5	18	12	25-12	13	31*2.5	78
10	5	4	5	1	5	1	5	5	5	1	25-5	20	12	25-12	13	33*2.5	83
11	4	4	5	1	5	1	5	4	4	1	23-5	18	11	25-11	14	32*2.5	80
12	4	2	4	1	5	1	5	5	5	1	23-5	18	10	25-10	15	33*2.5	83
13	3	4	4	1	4	2	4	4	4	1	19-5	14	12	25-12	13	27*2.5	68
14	3	5	4	1	5	1	4	4	4	1	20-5	15	12	25-12	13	28*2.5	70
15	5	4	5	1	5	1	5	3	5	1	25-5	20	10	25-10	15	35*2.5	88
16	5	4	5	1	5	1	5	4	5	1	25-5	20	11	25-11	14	34*2.5	85
17	4	4	4	2	4	1	4	4	4	1	20-5	15	12	25-12	13	28*2.5	70
18	4	4	5	1	4	1	3	4	4	1	20-5	15	11	25-11	14	29*2.5	73
19	5	5	5	1	5	1	5	4	4	1	24-5	19	12	25-12	13	32*2.5	80
20	3	4	4	1	4	1	4	4	4	1	19-5	14	11	25-11	14	28*2.5	70
21	4	3	5	1	5	1	5	3	5	1	24-5	19	9	25-9	16	35*2.5	86
22	4	3	3	1	4	1	4	4	4	1	19-5	14	10	25-10	15	29*2.5	73
23	4	4	4	1	4	1	4	4	4	1	24-5	19	11	25-11	14	33*2.5	83
24	4	4	4	1	4	1	4	4	4	1	24-5	19	11	25-11	14	33*2.5	83
25	4	4	4	1	4	1	4	4	4	1	24-5	19	11	25-11	14	33*2.5	83
26	5	4	4	1	4	1	4	4	4	1	22-5	17	11	25-11	14	31*2.5	78
27	4	4	5	1	4	1	4	4	4	1	22-5	17	11	25-11	14	31*2.5	78
28	4	4	4	1	4	1	4	4	4	1	20-5	15	11	25-11	14	29*2.5	73
29	3	4	5	1	3	2	5	4	5	1	21-5	16	12	25-12	13	29*2.5	73
30	4	4	4	1	3	1	3	3	3	1	17-5	12	10	25-10	15	27*2.5	68

SUS score is calculated using the following framework [65]:

- Add the total score for all odd-number questions, then subtract 5 for the X-value.
- Add up the total score for all even-number questions, then subtract that total from 25 to get the value of Y.
- Add up the total score of the new values (X+Y) and multiply by 2.5.

$$Average\ SUS\ Score = \frac{2316}{30} = 77.2 \quad (3)$$

The average SUS score for all the participants is 77.2, as calculated in (3), which indicates a good acceptance level of this software system. The highest SUS scores, which indicate excellent, are retrieved from 14 participants (U1, U3, U5, U8, U10, U11, U12, U15, U16, U19, U21, U23, U24, U25) where the values varied from 80.0 to 88.0. The lowest score, however, leaves a significant gap with 18 differences since the lowest value is 68. The lowest grade scale attained, which indicates okay, are acceptable values from 4 participants (U2, U4, U6, U13, U30). Based on the findings, it can be concluded that the software system has achieved an overall satisfaction level with an average SUS score of 77.2. However, its acceptability is at a marginal level, with a score of 68 on the SUS grading scale.

The development of a rule-based chatbot for early depression indication represents a significant advancement in leveraging AI for mental health support. By harnessing predefined rules and algorithms, the chatbot offers a transparent and interpretable approach to assessing users' mental states and providing appropriate interventions.

VI. Conclusion

The evolution of chatbot technology is trending, and it is beneficial in different application domains, including health. Technological intervention could assist in mental health, such as indicating depression as early as possible. In this study, state-of-the-art chatbots have been identified, such as the classification of a chatbot, a technique used by a chatbot, the fundamentals of a chatbot, the component architecture, and the challenges of chatbots so that the practitioner can have in-depth knowledge of how to develop them.

A rule-based chatbot is developed to assist in depression indication assessment for mental health-risk individuals at an early stage and provide the risky patient with appropriate support and resources. The right instrument tool is necessary to trace symptoms of depression. This study adopted the DASS21 instrument to develop the proposed chatbot. The rule-based technique has been implemented in the chatbot. It provides the features of depression indication assessment for users to self-screen for depression at the early detection and gives recommendations for the appropriate action, such as meeting a counselor. The operational process starts with the user's input. The chatbot will display options to allow the user to choose the most appropriate answer. The chatbot provides a depression sign screening assessment. The input from the user will be matched to the existing data in the chatbot depository before the calculation of results will be displayed.

Application evaluation is an essential criterion for any application development to ensure the application functions well and fulfills its objectives. The selected technique to evaluate this application is usability evaluation to ensure the system is well-functioning and provides the user's needs. The online questionnaire is given to thirty (30) respondents. The questionnaire consists of three (3) parts: demographic info, system usability scale (SUS), and suggestions from the respondents for future enhancement. Based on the SUS results, the rule-based chatbot has been accepted by all 30 respondents, with a good acceptance of an average SUS score of 77.2. In addition, other evaluations have been added, such as generating test cases to help improve the quality of the software. Evaluation results indicate promising accuracy and user acceptance, suggesting the potential of rule-based chatbots in aiding early self-depression indication and intervention. The chatbot is not a substitute for professional diagnosis treatment, and users are encouraged to seek help from mental health professionals for a comprehensive evaluation.

The development of a rule-based chatbot for early depression indication holds promise as an accessible and effective tool for identifying individuals at risk of depression. By leveraging established criteria and clinical knowledge, the chatbot offers a transparent and interpretable approach to assessing users' mental states and providing timely support and resources. This chatbot does not need to be trained to gain the data because it depends not on the previous data but on the specific rule. The user is guided to enter the necessary input and should be selected from the given option to avoid system failure.

Potential further improvement, such as using multiple languages to expand its usage to different races worldwide. More to the point, speech-based questions and responses for users who cannot read and type their queries. In addition, since users with mental health issues have sensitive emotions, hybrid rule-based and AI machine learning can be considered to detect the user's emotions. Ongoing and future research and development in this field hold the promise of advancing mental health care and improving outcomes for those dealing with depression.

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