

MOODLINK: A DATA-DRIVEN SOCIAL INTERACTIVE MOBILE APPLICATION FOR DEPRESSION RELIEF USING ARTIFICIAL INTELLIGENCE AND NATURAL LANGUAGE PROCESSING

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ABSTRACT

As adolescent suicide rates grew significantly in the past decade, depression, anxiety, and other mental disorders were largely held responsible for the growth [9]. However, these medical conditions are often overlooked during their early stages where symptoms are still remediable. Delayed or inattentive response to address the issue usually results in higher suicides rates or in lesser cases, mental ailments carried into adulthood. In an attempt to remedy the mental health crisis, countless mental health interventions are being introduced as means to mitigate the circumstances. In this project, we developed a mobile application that serves as a comprehensive therapy—journal and group therapy—for those struggling with mild to moderate depressive symptoms [10]. The application utilizes both the Sentimental AI and natural language processing in its backend server to generate accurate matches of users who share similar struggles, allowing users to connect and resonate with each other emotionally [11]. The application also provides a private and safe space for users to openly express their thoughts, alleviating their stress through daily journal entries.

KEYWORDS

Machine learning, Flutter, Adolescent Mental Health, Depression.

1. INTRODUCTION

A crucial stage of a person's mental wellness is developed during the period of adolescence where healthy social and emotional habits are formed. Currently, however, studies reported that one in seven 10-19 year-olds are struggling with at least one mental disorder. Among teenagers aged 15-19 years old, the fourth leading cause of death is suicide. Suicide rates have increased 30% in the past 20 years due to a variety of causes, such as mental illnesses and disabilities, most notably anxiety and depression [1]. A failure to address these mental health conditions among adolescents results in these ailments continuing into adulthood, as evidenced by Fombonne et al [2]. This causes a significant impairment in physical and mental faculties, becoming a contributor to growing suicide rates among adults as well. To remedy this growing mental health crisis among adolescents, mental health awareness, promotion, and prevention techniques are a key factor. Adolescents should be taught how to best regulate their emotions, build mental and

emotional resilience, and most importantly create and maintain positive and supportive social environments and networks.

Several techniques have been proposed in the past decades to deal with this mental health crisis, to varying levels of effectiveness. Antidepressants, for instance, saw clinical introduction in the 1950s. The drug sought to increase the activity of neurotransmitters, such as serotonin, dopamine, and norepinephrine, and help lessen depression and anxiety symptoms in patients. The usage has shown to improve a patient's mood and emotions, while also increasing one's appetite and concentration. However, while the drug improved depressive symptoms, side effects were observed: some had to be discontinued for certain patients due to insomnia, dry mouth, or nausea [3].

Online support groups, on the other hand, emerged as the new form of mental health counseling, allowing individuals to more conveniently express their struggles and feelings through virtual platforms. Even without face-to-face interaction with the other individuals, the method proved to be a source of individual empowerment and collective group identity. However, this effectiveness can occasionally be limited, as Wentzer and Bygholm stated in their study: online support groups showed improvement “not for collective empowerment” [4].

With the rise of new social media platforms, some tried to extend public engagement about mental health issues by heavily utilizing hashtags on platforms, such as Instagram. Mental health awareness campaigns across many social media platforms are conducted annually. Instead of finding how the public engages collectively and building a coherent sense of community concerned with mental illnesses, McCosker and Gerrard found that only 15% of users in these campaigns were considered legitimately depressed [5]. The rest, they found, had profile activity indicative of socially engineered depression made namely to garner attention. Only a minority of social media posts in the data set revealed real signs of mental struggles, usually lacking heavy use of hashtags. This discovery demonstrated that social media have the potential to demean the purpose of those who are in fact experiencing depressive symptoms.

Our approach to this method is a lightweight social media engineered to fit the needs of those with depression and anxiety [15]. This application combines multiple aspects of previously stated approaches, namely journaling as well as mental health awareness through social media interactions. The end goal of this application is to allow users to express frustrations and mental struggles through both private and public interactions with other like-minded users. Users will be able to discuss their own mental state through an electronic journaling system. On the public interaction side, users are matched up through a sentiment analysis algorithm, which will recommend users based on shared content between sets of posts. We believe that matching users up and letting them communicate and understand each other will help promote an inclusive and supportive environment.

In two application scenarios, we demonstrate how the above combination of techniques. The rest of the paper is organized as follows: Section 2 discusses the challenges in this research as well as during the experimentation phase of our AI; Section 3 describes our methodology and solution to those challenges through a mobile application and backend server; Section 4 displays the experiments we completed to test the accuracy of the AI backend server we created; Section 5 compares our solution to other app-based mental health interventions and experiments. Finally, Section 6 concludes the study and states future work of this project.

2. CHALLENGES

In order to build the project, a few challenges have been identified as follows.

2.1. The Complexity of Partner Recommendation Systems and Sentimental Analysis

Traditional social media's friend recommendation is often based on various factors, such as: the user's phone contact, search history, mutual friends, followings [12]. However, for the specific purpose of this application, friends' recommendations need to be tailored to the user's circumstances. As one major goal of this application is to pair up users who share similar emotions or experiences so that they can resonate with each other, the application needs to use a backend AI—the Sentimental AI—to make accurate match-ups based on the tone and content of the user's journal entries. However, since most users of this app are expected to have negative behavior, the effectiveness of using a sentimentality analysis AI is limited, as most posts would be registered as sad. Natural language processing is another option to consider, which analyzes content instead of emotion. Natural language processing will be able to grasp certain subjects such as interests, passions, and frustrations to a given level of specificity.

2.2. Compromises Between User Privacy and Robust User Interaction

In order to create a safe, personal space for users to freely express their emotions without the concerns for others' comments, the application will need a degree of user privacy. However, one potential issue for a system such as this is that users may not receive any attention if their account is too private. Inversely, users may also receive unwanted attention if they make their account public. Reaching a balance or a compromise between these two situations can be tricky to accomplish. For an app centered around privacy, it can be difficult to determine the length to which users can interact with each other. Users cannot simply befriend and start conversations with everyone from their recommended friend list because that becomes an invasion of other's privacy. Likewise, users should not be able to see others' posts should they contain private information. Hence, in order to start a conversation, the user needs to send a friend request that needs to be manually accepted by the other user in order for the conversation to begin. Guaranteeing this level of user privacy, the application helps to encourage a safe space and a positive environment.

2.3. User Experience and Associated Ideal Use Case with User Retention in Mind

In order to maintain a positive user experience, the application will need to include an intuitive user interface. To avoid users finding the application confusing to navigate due to over-complicated app features, the interface will require navigation bars that help segment the application into simple chunks. Intrusive and useless features, such as ads and constant notifications, will need to be eliminated. Instead, features that meet user needs, such as communication and posts, will be preserved to create a simple, clean app design that improves user experience. The intended use case of the app must also be taken into consideration. Users ideally should use this application in short bursts during times of stress or generally semi-daily use. Users should spend half of their time journaling and the other half of their time chatting with others. The app must be designed with this use case in mind to keep user retention high. Otherwise users may grow overwhelmed or impatient within the first couple days of use and give up on using it.

3. SOLUTION

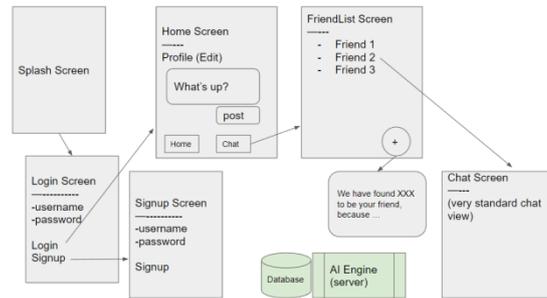


Figure 1. Overview of the solution

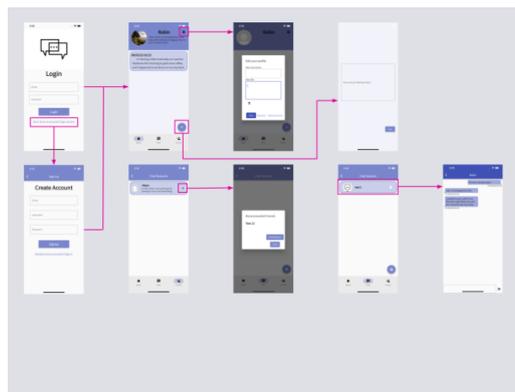


Figure 2. Screenshot of using process

3 Purposes

- allow user alleviate stress through journal entries by offering them a private place to express their emotions
- accurately match users who share similar emotions/experiences by analyzing journal entries using sentimental AI
- allow users to communicate and resonant with each other (mimics self-help group in therapy)

3 Components

- frontend application (Dart in Flutter)
 - 3 sections:
 - Journal entry page
 - recommended friends page
 - chat page
- backend cloud database (Firebase)
 - Realtime database
 - storage
 - authentication
- backend machine learning server (Sentimental AI written in Python)

- access data gathered to analyze the emotional tone and match users who have similar emotions

This application provides a safe, personal space to help users alleviate stress through journal entries and accurately matches up users who share similar emotions or experiences so that they can resonate with each other. The application relies upon three central components: the frontend application, which is done through Flutter; the backend cloud database, which is done through Firebase, and the backend machine learning server, which assists in user recommendation.

The frontend is only accessible if the user is authenticated by Firebase's Authentication service [13]. This is done through a simple login system. To sign up, users will only have to provide an email address and a password. The frontend itself consists of a journal entry section, a friend recommendation section, and a chat section. On the user's profile page, they can view their entries from most recent, as well as change their profile info, such as user name, description, and profile picture. Users will have to write at least one post in their journal in order to access the recommendation system in the friends page. This page relies on a backend machine learning server which will use sentiment analysis to determine which user is most similar to the current user based on post content. The resulting recommendation is shown to the user for them to send an invite if they would like. After an invite is sent and the other user accepts the friend request from their end, then both users are able to communicate in a chat screen which functions similarly to standard chat screens present in applications such as WhatsApp and WeChat. User profile information, user journals, and chat logs are all stored within Firebase's Realtime Database service with appropriate rules to ensure privacy.

```
Future <void> sendMessage() async {
  await FirebaseDatabase.instance.ref().child("userChat/" + convoName + "/" + DateTime.now().millisecondsSinceEpoch.toString())
    .set({
      'timestamp' : DateTime.now().millisecondsSinceEpoch,
      'author' : FirebaseAuth.instance.currentUser!.uid,
      'content' : ChatController.text,
    });
  print("message sent");
  ChatController.text = '';
  ChatController.text = '';
  }).catchError((error){
    print("failed to send the message");
  });
}
```

Figure 3. Screenshot of code 1

For this specific project, Google Firebase is used as a platform that offers an active backend for analytic, authentication, databases, fire storage and more. Its Realtime Database service enables the application to store and sync data between users in real time, consisting of five subdirectories: userChat, userFriend, userInvite, userPost, and userProfile. Each subdirectory has its own properties, some of which have their own sub-collections. For example, userChat stores chat content by organizing each conversation under a key name that is a combination of each users' User Identification code (UIDS). Then under each ConvoName, a subcategory is created using the timestamp the message is sent. This organization based on timestamp allows the application to display messages by its chronological order on the chat screen. The timestamp category then contains the actual content of the message, its author, and its timestamp so that when data is queried, the application displays messages based on the chronological sender and time. A successful message will be printed in the console if the message is recorded in the realtime database; if not, a failure message will be shown. By storing the conversation messages into the realtime database in an organized manner, the application can extract the information more efficiently and display them logically. The above piece of code is meant for sending messages. It creates a new list of key/values pairs within the Realtime Database containing all the appropriate

metadata per message. The address of this message is within userChats, within the corresponding convoName.

```

Future<dynamic> sentimentFriendSelector() async {
  String url = "https://userpostsentimentanalysis.marisabelchang.repl.co/" + getUID();
  String pickedUID;
  String pickedName = "";
  String pickedDescription = "";

  //Get a UID from the server
  var response = await http.get(Uri.parse(url));
  print(response.body.toString());
  var listData = jsonDecode(response.body.toString());

  pickedUID = listData[0].toString();
  if (pickedUID == getUID())
  {
    pickedUID = listData[1].toString();
  }
  print("RESULT: " + listData.toString());

  //Get the username and description
  await FirebaseDatabase.instance.ref().child("userProfile").child(pickedUID).once()
    .then((event) {
      print("Successfully grabbed profile for user: " + pickedUID);
      var profile = event.snapshot.value as Map;

      pickedName = profile["Username"];
      pickedDescription = profile["Description"];

      print(pickedName);
      print(pickedDescription);
    }).catchError((onError) {
      print("Could not grab user profile for user " + pickedUID);
    });

  return [pickedUID, pickedName, pickedDescription];
}

```

Figure 4. Screenshot of code 2

This application's backend consists of both the Google Firebase and the Sentimental AI hosted by a Python server that is running flask. To structure an accurate friend recommendation system, the Firebase and the Python server consistently communicate with each other. Because the user data is stored in the Firebase, the Python server will have to access and read data from the database before producing the analyzed results. Sentimental Analysis is a type of machine learning algorithm that can calculate the "polarity" of a given piece of text. A common use is to determine user satisfaction. A specification of sentimental analysis, called Natural Language Processing, can be used to determine the topic discussed instead of emotion, though it is still calculated as a polarity score. Using Flask, a Python server library, the server hosts the Sentimental Analysis AI, which then reads through all posts made by the user and determines its polarity for each post. The AI proceeds to calculate the user's own polarity and selects one user from the database whose polarity best matches the target user. During this process, the AI filters out the user's friends to avoid recommending a friend who already exists in the target user's friend list. After producing the best match, the Python server makes a Firebase call to the Realtime database's userProfile subdirectory in order to display the recommended friend's information to the user.

4. EXPERIMENT

4.1. Experiment 1

In order to evaluate the accuracy of the friend recommendation system, we tested the Sentimental AI in various scenarios. For this experiment, we utilized synthetic data, which were 15 test subjects divided into five groups ranging from experiencing negative, neutral, to positive

emotions. The scale for these emotions were chosen arbitrarily. Subjects 1, 2, and 3 from Group 1 exhibit extreme depressive symptoms while Subjects 4, 5, and 6 from Group 2 exhibit moderate depressive symptoms. The inverse characteristic occurs for groups 4 and 5. Group 3 is considered to be neutral. One journal entry displaying the corresponding emotion will be posted by each test subject and stored into the Google Firebase. The Sentimental AI will then proceed to make friend recommendations based on the tone and content analyzed from each journal entry, and matching results for each test subject will be recorded. Data is processed according to the proximity of the recommendation — recommendations of members within a group are considered “exact.” Recommendations for a member one group away (e.g. a Group 2 member being recommended a Group 1 member) is considered “close.” Anything else will be considered an inaccurate recommendation.

Proximity	Percentage (%)		
	1 Post	3 Posts	5 Posts
Exact Matches (In same group)	26.7	33.3	33.3
Close Matches (1 group away)	40	40	46.7
Inaccurate Matches (>1 group away)	33.3	26.7	20

Figure 5. Table of proximity vs accuracy

Proximity vs Accuracy for Groups containing 1, 3, and 5 Posts Respectively

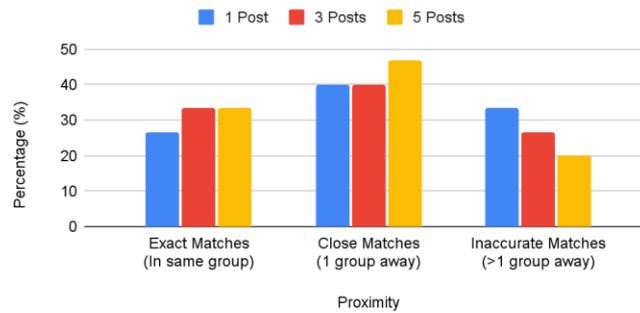


Figure 6. Graph of proximity vs accuracy

Post Amount	General Accuracy (%)
1 Post	66.7
3 Posts	73.3
5 Posts	80

Figure 7. Table of post amount vs general accuracy

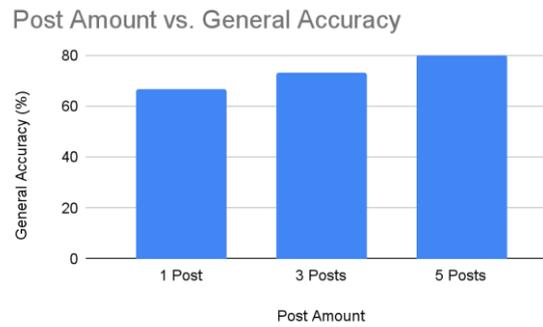


Figure 8. Graph of post amount vs general accuracy

The results indicate several interesting conclusions. Trials for 3 and 5 posts had the highest frequency of exact matches, at 33.3% each. The 1 post trial had the worst accuracy of exact matches, at 26.7%. Trials for 1 post and 3 posts tied in frequency with regards to close matches at 40%. The 5 post trials scored the highest frequency for close matches at 46.7%. For inaccurate matches, the 1 post trial scored the worst, at 33.3% inaccuracy. This is followed up by the 3 post trial, at 26.7% inaccuracy, and the 5 post trial, at 20% inaccuracy. As such, accuracy in this experiment can also be said to be generally proportional to the amount of posts that users made. When determining overall accuracy by combining the frequency of exact and close matches as a percentage, the 1 post trial was the least accurate at 66.7% accurate, the 3 post trial at 73.3%, and the 5 post trial at 80% accurate. Regardless of trial, however, close matches were the most frequent recommendation.

4.2. Experiment 2

In addition to checking the artificial intelligence's accuracy, it is also important for us to check if our implementation of therapy methodologies (including our artificial intelligence) is successful or not. To do this, we designed another experiment that will look at user happiness and stress level prior to using the app and the resultant levels after using the application. 10 test subjects for this experiment were given a simple questionnaire after testing out the application. The questionnaire asked participants questions pertaining to stress level and satisfaction with the app. Participants were asked to answer such questions from a grading scale of 1-5.

Test Subject	On a scale 1-5, how stressful have you been feeling before using the app?	On a scale 1-5, how happy did you feel before using the app?	On a scale 1-5, do you find this app helpful in improving your mental health?	After using the app, how stressful do you feel on a scale 1-5?	After using the app, how happy do you feel on a scale 1-5?
1	4	2	3	3	3
2	2	3	1	2	2
3	5	2	4	4	3
4	3	4	3	2	4
5	2	2	2	2	2
6	3	2	4	1	3
7	3	2	2	2	2
8	4	1	5	3	2
9	5	1	4	3	1
10	1	2	2	1	2
average	3.2	2.1	3.0	2.3	2.4

Figure 9. Table of test subject

Emotions	Percentage(%)		
	Decreased	No Change	Increased
Stress Level	70	30	0
Happiness Level	10	40	50

Figure 10. Table of emotions change

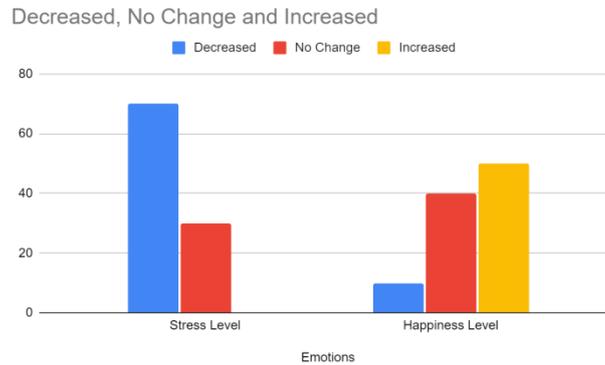


Figure 11. Graph of Emotion change

The table and the graph display a few interesting trends. The test subjects responded most positively to the decrease in stress level, as reflected by a reduced average stress rating from 3.2 to 2.3 after the usage of the application. The graph also demonstrates this trait as no test subjects are shown to report an increase in stress. On the other hand, happiness level sees an increase from an average of 2.1 to 2.4; however, 10% of the test subjects stated a decrease in happiness level while 40% reported no change. This may be caused by the test subject's unfamiliarity with the app features as they were still adjusting to the new form of mental health intervention. Overall, the test subjects rated 3.0 on the effectiveness of the application on their mental health: 70% reported reduced stress, and 50% displayed improved happiness.

Both experiments yielded moderately positive results, exhibiting a general success of the application. Experiment 4.1 saw that the accuracy of the friend recommendation system is directly proportional to the amount of journal entries an user has: the highest frequency of exact matches was with the 5 post trials at 46.7%. The experiment also concluded that if a user has five entries, the AI can generally guarantee 80% matches to fall within at most one group of the target users. Experiment 4.2 displayed 70% reduced stress level and 50% increased happiness level among test subjects after the usage of the application. However, 10% of subjects reported decreased happiness levels. The subjects' unfamiliarity with the app features might have contributed to the negative feedback.

5. RELATED WORK

Mohr et al. for this study performed an extensive coaching experiment using their own app suite called Intellicare [6]. Unlike our application, Intellicare has multiple applications instead of just one. Researchers found that bundling several apps into a comprehensive self-care package was successful in alleviating depression and anxiety (Mohr et al, 2017). Intellicare is also focused more on active self-betterment and coaching rather than our application, which focuses more on user interactions and journaling. According to the researchers, "...apps tend to use simple interactions, are quick to use, and support a single or limited set of related tasks" (Mohr et al,

2017). Our application aims for more engagement than theirs by acting as a chat discussion app as well as an app to privately post and use as a safe space. Researchers for this study also extensively used coaching as an experiment method (Mohr et al, 2017). Our application similarly emphasizes constant communication and assistance, as it is built into the app's infrastructure.

Birney et al. propose a mobile web app called MoodHacker, which utilizes cognitive behavioral therapy skills, to help reduce negative cognitions for working adults who suffer from depression [7]. The app produced significant results: improvement on testing subjects' depression symptoms and other workplace-induced negative cognitions (Birney et al, 2016). Instead of focusing on adolescent's mental health related issues, this paper aims to develop a mobile application catered towards working adults in the United States, who amount for an estimated \$210.5 billion in productivity loss (Birney et al, 2016). According to the researchers, the mobile web app seeks to "develop effective interventions that can be more widely disseminated ... and directly to individuals who will not seek face-to-face care" (Birney et al, 2016). Our application shares a similar objective: allowing adolescents who suffer from mental health issues to communicate and resonate with each other in a virtual setting where in-person interaction is not needed.

Fuller-Tyszkiewicz et al. seeks to evaluate the usability of a mental health application by having three groups—diagnosed individuals who suffer from depression, professionals such as doctors, and specialized mental health researchers—to rate the application in terms of its quantitative and qualitative impact on its users [8]. The study found that the two expert groups favored app features that emphasize self-betterment and serve as cognitive treatment for the users but showed their concern for the challenging self-navigation of the application (Tyszkiewicz et al, 2018). This paper highlights the importance of the functionality of mental health applications by implementing simple self-navigation features (Tyszkiewicz et al, 2018). Our application reflects this by setting up an intuitive user interface that contains only necessary features organized in a coherent fashion, greatly optimizing user experience by eliminating overcomplicated app design. According to the researchers, the usability of the application is vital because "perceptions of navigability and quality of content are likely to impact participant engagement and treatment compliance" (Tyszkiewicz et al, 2018).

6. CONCLUSIONS

In summary, our method was to develop a mobile application which serves as a comprehensive therapy application for those suffering from depression [14]. This application is connected to a backend server that utilizes natural language processing to recommend people to those that share their interests and struggles. This Sentimental AI makes friend recommendations by accessing data from the cloud database, the Google Firebase, and analyzing the content and emotional tone. The app also includes journal therapy and group therapy techniques within its features. The application seeks to alleviate stress by providing a safe, private space for users to freely express their thoughts and emotions while also allowing users to resonate with one another. Two experiments were conducted to determine the objective and subjective accuracy of the backend AI server. The first experiment utilized fabricated journal entries created by users—who showed varying levels of emotions—and recorded the matching results generated by the Sentimental AI. The experiment results supported the fact that matching accuracy is usually directly proportional to the number of entries an user made: 5 posts revealed 80% general accuracy while 1 post was only 66% accurate. The questionnaire revealed that 80% of users felt less stressed and 50% of users felt happier after using the app. These results indicate that the AI is at least both generally accurate and effective at bolstering user interaction and satisfaction. The experiments conducted solved challenges brought up prior by both analyzing potential concerns with the accuracy of the

artificial intelligence backend but also with the user experience of the app in relation to the AI system implemented.

As evidenced by our experiments on AI accuracy, the accuracy of the natural language processing algorithm used in our backend server could be better optimized and more robust. It is able to pick up on general topics but can struggle when given posts with minimal data and also struggles with picking up on fine details. The AI recommendation system as a whole may also not be utilized well enough by the user base if they do not consider the application to be useful enough. In regards to the app's frontend, more quality of life features could also be added to the application to better ensure user satisfaction when it comes to user experience.

As we collect more real data from the influx of new users, further experimentation will be conducted to improve the accuracy of the Sentimental AI. Its limitation will be addressed as we explore the possibility of increasing the AI's capability of analyzing content in more details when it is given minimal data. Moreover, updates on the application itself will be added in an attempt to improve user experience. We hope to provide users not only an effective but also friendly app.

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