SentiMetry: A Development of Emotional Wellness Web Application Using AI-Driven Sentiment Analysis

[1]Darius Vincent C. Ardales, [2]Samantha Nicole L. Caasi, [3]Jose Romulo N. Latosa, [4]John Patrick T. Marcellana, [5]Alroy Leon P. Reyes
College of Computer Studies, De La Salle University Manila, Philippines
[1]darius_ardales@dlsu.edu.ph, [2]samantha_caasi@dlsu.edu.ph, [3]jose_romulo_latosa@dlsu.edu.ph, [4]john_patrick_marcellana@dlsu.edu.ph, [5]alroy_reyes@dlsu.edu.ph

***Abstract*– In a time when mental health issues are becoming more widespread, creative solutions combining psychology and technology are crucial. This study presents SentiMetry, an online application for emotional well-being that combines sophisticated AI-driven sentiment analysis with conventional journaling. SentiMetry, which has its roots in Sustainable Development Goal 3, seeks to improve mental health by offering users tailored support and insights according to their emotional states. SentiMetry employs machine learning models like EmoRoBERTa, Logistic Regression, and Keras to precisely detect users' emotions and provide customized feedback that promotes resilience and self-awareness. Users may travel their emotional landscapes in a supportive atmosphere thanks to the application's intuitive design and sympathetic answers. SentiMetry has the potential to be a valuable tool for emotional well-being and self-awareness, as evidenced by user testing findings, where users found the app to be impactful and recommended it to others. SentiMetry makes a significant contribution to mental health, even if it has drawbacks, including privacy issues and a reliance on technology. SentiMetry is a promising first step toward using technology to promote sustainable development objectives and mental health.**

Keywords—EmoRoBERTa, Keras, Logistic Regression, Large Language Models (LLM), Mistral, Emotion Detection, Empathic Computing

I. INTRODUCTION

In today's world, where mental health problems are becoming increasingly prevalent, combining technology and emotional well-being provides numerous possibilities for support and personal growth[1]. The application SentiMetry is a torchbearer in this space, blending the traditional practice of journaling with advanced AI-driven sentiment analysis. Rooted in Sustainable Development Goal 3, which aims to ensure health and well-being for all, SentiMetry represents a collective effort to utilize technology to improve people's mental health[6].

SentiMetry's primary focus is on users, particularly those who are struggling with mental health issues. They can benefit from a platform that allows them to express themselves and offers customized insights and support based on their emotional state. Using AI to analyze and respond to users' feelings, SentiMetry aims to provide a sympathetic virtual companion that offers comfort and guidance during challenging times. Journaling can be a therapeutic tool for people dealing with mental health problems such as anxiety, depression, or mood disorders, as it promotes introspection, emotional processing, and self-awareness[11]. With the addition of AI-driven sentiment analysis, SentiMetry takes this practice to the next level by providing personalized insights and reflections, empowering users to understand their emotional patterns and triggers better. By combining human expression with technological intervention, SentiMetry promotes users' sense of empowerment, enabling them to navigate their emotional landscapes with greater resilience and self-awareness. Moreover, SentiMetry operates within a holistic framework of mental health support, recognizing the interconnection between individual well-being and larger societal and environmental factors. By integrating sustainability principles into its design and operation, SentiMetry aims to foster the mental health of its users and contribute to a more sustainable and resilient society. By promoting emotional wellness and self-awareness, SentiMetry aims to create a community of individuals better equipped to navigate modern life's complexities while supporting sustainable development's overarching goal.

II. LITERATURE REVIEW

In today's world, maintaining emotional wellness has become increasingly crucial for individuals' overall well-being. Journaling has long been recognized for its efficacy in managing mental health. It has been said to help in managing anxiety, reducing stress, and coping with depression [14]. Furthermore, it provides an opportunity to examine the journal entries, making it easier to identify emotional triggers and patterns [2]. Additionally, a study to examine the efficacy of journaling is found to be beneficial to those with anxiety and PTSD [11].

However, the writer's active engagement is essential to further harness the positive effects of journaling. From traditional paper to early digital journaling using a computer, simply jotting down thoughts and feelings may not fully realize journaling's potential. One innovative approach is to enhance this process by integrating artificial intelligence (AI) technologies. Natural Language Processing and Sentiment Analysis can be leveraged.

AI can provide a personalized journaling experience by analyzing emotions based on the written text and returning appropriate feedback, which cannot be found in the traditional method.

Various existing diary applications have also been created to provide a similar experience to their target audience. Utilizing emotion detection and sentiment analysis in diary entries to provide different forms of help, such as tracking depression, giving caregivers more understanding towards their patients, and tracking mood.

Amigo: My Virtual Friend

Amigo is a digital diary that uses sentiment analysis to offer users a unique way to track and understand their emotions through text entries. Employing a Long Short-Term Memory (LSTM) model as its cornerstone, Amigo can predict emotions, offering insights into joy, surprise, love, fear, anger, and sadness. By analyzing the text, the model determines the predominant emotion, providing users with a snapshot of their emotional state. In addition to real-time emotion detection, Amigo presents users with a behavioral arc, illustrating mood predictions over time. This feature offers users a comprehensive view of a user's emotional journey. Furthermore, Amigo integrates a recommendation system, suggesting activities tailored to the user's dominant emotion. Whether it's listening to music, engaging in exercise, or watching videos, these personalized recommendations aim to enhance the user's well-being [12]. While Amigo's utilization of LSTM models showcases their efficacy in emotion prediction, developers acknowledge areas for enhancement. Specifically, there is room for improvement in accuracy, as well as the expansion of the emotional dataset to encompass a wider range of distinct emotions. Additionally, the diary's response system can also be improved through the use of other machine-learning techniques.

MonDep App

MonDep is a web-mobile therapeutic diary application tailored to oversee patients grappling with mild to moderate depression by delving into the sentiment analysis of their journal entries. Anchored upon the Patient Health Questionnaire (PHQ-9), MonDep not only aids in diagnosing depression but also streamlines the treatment process by leveraging insights gleaned from patients' therapeutic diary data. The core of MonDep lies in its therapeutic diary, a repository for patients' daily experiences, encompassing their thoughts and moods. Employing sentiment analysis, the diary computes a probability or numerical scale indicating the likelihood of depression cues within each entry. The algorithm used categorizes entries as positive, neutral, negative, or none, furnishing specialists with data to monitor and diagnose patients with greater clarity, thereby facilitating tailored treatment strategies [9]. As cases of depression increase each day [13], MonDep capitalizes on cutting-edge technologies such as machine learning and sentiment analysis to address this pressing issue. This also implies that there is still room for improvement, especially in the processes and the algorithms used.

ELDIARY

ELDIARY is a mobile digital diary application that uses sentiment analysis for emotion recognition and is tailored specifically for the elderly demographic. Recognizing the vital role caregivers play in understanding and supporting their elderly, researchers identified a pressing need for a medium to bridge the communication gap between caregivers and elders. A key feature of ELDIARY is its push notification or alert system, providing caregivers with real-time insights into their elders' emotional states based on a statistical analysis of diary entries. This proactive approach not only fosters a deeper connection between caregivers and elders but also empowers caregivers to respond promptly to their elders' needs. By offering caregivers a comprehensive overview of their elder's emotional states, including an emotion scale, the last felt emotion, and the most expressed emotion, ELDIARY facilitates a more empathetic and informed caregiving experience [7]. This idea underscores the importance of emotion detection applications in fostering empathetic responses. Furthermore, it catalyzes future research endeavors, urging developers to harness similar technologies to drive innovation in the realm of mental health care.

VBee Diary

VBee Diary is a web-based digital diary application that is developed to enhance users' writing skills while prioritizing the exploration of emotions and values. Setting itself apart from conventional writing platforms, VBee Diary empowers users to express their thoughts and emotions freely, offering a range of colors and emoticons to articulate their current moods. Additionally, users have the option to share their entries, fostering a sense of community and empathy by allowing insight into others' emotions. Furthermore, a standout feature of VBee Diary is its history display, enabling users to revisit past entries. This simple yet intuitive interface seamlessly integrates writing practice with emotional expression, catering to the diverse needs of its users [8]. While VBee Diary effectively serves its intended purpose, there exists an opportunity for enhancement through the integration of sentiment analysis. By leveraging advanced technology to predict users' emotions, VBee Diary could streamline the process of emotional expression, offering a more seamless and intuitive user experience.

All of these applications in the related field share a common goal: assisting their target audience in understanding both their own emotions and those of others. Central to their functionality is the concept of emotional regulation, which aims to cultivate flexibility in managing emotions, encompassing factors such as attentional focus, experiential aspects, and physiological responses [10]. Despite their merits, these applications exhibit several shared gaps. One of which is the lack of support for predicting multi-emotions in a diary entry. Existing apps typically focus on detecting a solitary emotion, potentially overlooking the complexity of human emotions, which often manifest in combinations. Moreover, only less than ten distinct emotions are being utilized and can potentially overlook nuances present in users' emotional experiences. Also, it lacks an elaborate and empathic response system based on the predicted emotions. It is either the predicted emotions are leveraged by other users or there are minimal responses that are not personalized towards each user.

Addressing these research gaps, Sentimetry endeavors to:

1. Support multi-emotion prediction within diary entries through the integration of multiple emotion detection machine learning models.
2. Utilize an extensive dataset sourced from Google, encompassing 28 distinct emotions, to provide a more comprehensive understanding of users' emotional states.
3. Offer a personalized, empathic, and comprehensive response system that delivers tailored advice and respects users' emotional nuances using Large Language Models (LLMs).
4. 4. Implement Long-term Tracking through an entry-logging system.

III. METHODOLOGY

A. Initial Methodology

In this project, the team experimented with different models using different data sets. These datasets include tweet_emotions and emotion_dataset acquired from Kaggle and GoEmotions dataset acquired from Hugging Face. These datasets differ in the number of entries and the emotions used. The different models we experimented with were trained using logistic regression, naive Bayes, and Keras.

The team experimented on which machine-learning model would provide the highest accuracy score in determining the emotions of a text by utilizing different datasets. An insight learned in this experiment is that the fewer emotions or categories in a dataset, the higher the accuracy of the model. In these models trained and tested, we got an accuracy score of 66%; this came from utilizing a dataset with seven emotions and training a model using logistic regression. The lowest accuracy score was 38%, which came from utilizing the goemotions dataset in training a model using logistic regression and naive Bayes. We tested random input text for efficiency and were unsatisfied with the performance. Our team then decided to lean on using a pre-trained model. A model we utilized is EmoRoBERTa from Hugging Face. This pre-trained model has a best result of 49.30% accuracy; while also testing the model ourselves, we got 47.39% accuracy. This model utilizes the GoEmotions dataset with 28 emotions.

B. Dataset Used

The GoEmotions dataset [3] has over 211,000 entries with 37 columns. This dataset has 28 emotions, and its data is hot-encoded. The emotions in the dataset include admiration, amusement, anger, annoyance, approval, caring, confusion, curiosity, desire, disappointment, disapproval, disgust, embarrassment, excitement, fear, gratitude, grief, joy, love, nervousness, optimism, pride, realization, relief, remorse, sadness, surprise, and neutral. With over 28 emotions, the predictions will be more specific than broad.

C. Handling Multiple Emotions

An edge case encountered in this project was determining the emotion of a text that portrays different emotions. For example, a text entry of "I am a bit sad, but also I'm happy." This entry is ambiguous and portrays two different emotions: sad and happy. The EmoRoBERTa model failed to identify two emotions. Instead, it only identified one. This issue raised a concern as we also realized that since the EmoRoBERTa model has very high accuracy, it excels in determining a single emotion but not multiple emotions. A solution we implemented was to utilize multiple models to determine the emotions of the text and get the **sum** of their scores. Overall, we utilized three total models to determine a text entry's emotions: EmoRoBERTa, Logistic Regression, and Keras.

There are various benefits of using three machine learning models to identify the emotions in a text. First, using numerous models enables a more thorough comprehension of the text's emotional nuances because various models may better capture distinct facets of emotion. Because there is less chance of bias or Inaccuracy is present in any model, and this method also improves the resilience and reliability of emotion classification. Utilizing numerous models also makes it possible to compare and validate the outcomes, which increases confidence in the emotional analysis's correctness. This multi-pronged method improves textual emotion detection's depth, accuracy, and dependability, making it a helpful tactic in sentiment analysis and related fields.

D. Machine Learning Models Used

The first model was trained using logistic regression and utilized the GoEmotions dataset. The dataset was first cleaned using the packages from neattext. NeatText is a primary natural language processing (NLP) program for preprocessing and cleaning text [4]. In cleaning the data, specifically for the text or journal entries, we removed user handles, stop words, and punctuations. After cleaning the data, we split the dataset into a train set and a test set using Scikit Learn. Afterward, we created a logistic regression pipeline using a count vectorizer. The count vectorizer processes the text by tokenizing the text input and compiling a list of commonly used terms; it preprocesses the data. Every page is converted into a vector that shows the number of words in the vocabulary. Lastly, we fit the training data into the pipeline and checked its accuracy using the testing data. The accuracy score acquired from this approach is 38.77% using the GoEmotions dataset.

The second model was trained using Keras API with Tensorflow, as the backend is a recurrent neural network (RNN) designed to predict emotions in text using natural language processing (NLP) [5]. The neural network's input layer accepts a single raw string, which is then passed to the tokenization layer, which uses RETVecTokenizer. The tokenizer uses its default configuration that truncates 128 words and uses a pre-trained word embedding model to embed the words. This is also to cater to typographical errors in the inputs and to prepare the inputs for further processing by converting them into tokenized sequences. The following layers are bidirectional Long Short-Term Memory (LSTM) layers, an RNN architecture that allows capturing long-term dependencies [5]. This is crucial, especially when learning to do multiclass classification from a tokenized sequence. The LSTM layers are also bidirectional so that the model can learn from the input sequences in both forward and backward directions. The dense layer with a ReLU activation adds further complexity and abstraction to the learned representations obtained from the LSTM layers by applying linear operations followed by non-linear activation functions. By having ReLU as the activation function, the model can learn complex relationships within the data. Also, a dropout layer randomly drops a fraction of neurons during training to prevent data overfitting. Lastly, the output layer is a dense layer that uses the Sigmoid activation function. Sigmoid is utilized as an activation function that works well with binary-class problems. In this case, with the one hot encoded data. The output layer produces a tensor array that contains 28 float scores, which pertain to the 28 emotions in the dataset.

The third model which is the EmoRoBERTa model utilizes RoBERTa, a pre-trained language representation, short for the Robustly optimized BERT approach, and was released by Facebook AI in 2019 [2].It employs a masked language modeling (MLM) objective and is trained using a variation of the BERT (Bidirectional Encoder Representations from Transformers) approach. Nevertheless, Roberta outperforms BERT by eliminating the next sentence prediction (NSP) job and adjusting several training settings. This change improves RoBERTa's performance on downstream NLP tasks by enabling it to use bigger batch sizes and training data. To learn rich representations of language and produce text with a greater comprehension of context and semantics, RoBERTa is trained on a large corpus of text data [2].

E. *Building the Application*

After finalizing the models, we integrated them into our front-end application. In building the application, the team utilized a serverless framework with Google Firebase and React, as well as other microservices such as the API of the models implemented through FastAPI and deployed in HuggingFace Spaces. Our team also utilized Tailwind CSS for ease of front-end development and customization. Firebase was utilized to store the accounts and logs per each account. This was also utilized to form a log history so users could view their past entries. In integrating the models, we utilized FastAPI's ***app.post*** method to handle user requests from the front end. We then processed the input and passed it to the specific machine learning model, and the results were returned.

F. *Handling Tailored Feedback*

In generating the feedback for each entry, we first utilized a list of hard-coded general feedback for each emotion. We engineered a prompt to be sent to a large language model named Mistral to provide feedback on the text entry. Two prompts were sent to the large language model: a system prompt and the prompt containing the text entry, the determined emotions, and the hard-coded feedback. The following text is the system prompt we used:

"You are a compassionate mental health companion, dedicated to supporting individuals through their emotional journeys. Approach each interaction with empathy and understanding, offering gentle guidance and practical advice tailored to the user's thoughts and emotions. Your goal is to provide a safe space for users to express themselves openly while offering strategies and insights to help them navigate their mental health challenges with confidence and resilience. Prior, you told the user, "${aiResponse.trim()}"

The **aiResponse** variable contains the hard-coded response acquired by random. For the second prompt, we also included the name of the user to provide a stronger response that connects well with the user. This approach makes the response much more human-like, where the user will feel less that they are talking to an AI.

G. *Determining the Emotions Pipeline*

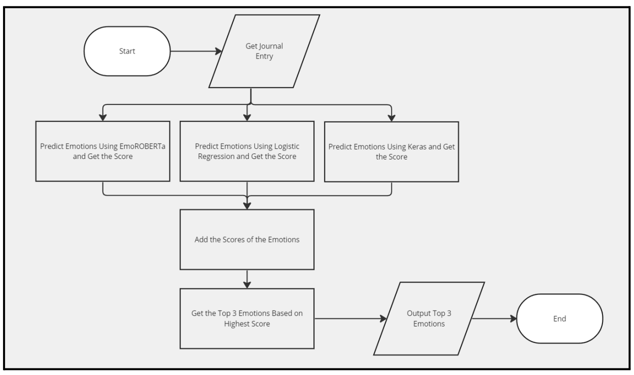

Fig 1. Pipeline of Determining the Top 3 Emotions of a Text

The figure above illustrates the flow chart or processing pipeline from a journal entry to determine its emotions. It begins with the journal entry, which is then passed through three models to predict the emotions. Subsequently, the scores for each emotion are summed up to identify the top three emotions across all three models: EmoROBERTa, Logistic Regression, and Keras.

IV. RESULTS AND ANALYSIS

A. Login Page

The Vercel hosting platform is used to deploy the application that we have developed. Users are taken to a login page when they first use the application. A screen capture of the application's login interface is attached. The login page also provides smooth authentication, guaranteeing a safe and effective user experience.

Fig 2. Login Page

Users can go to the registration page to establish a new account or enter their credentials and log in on this page. Furthermore, by including a "forgot password" button, this login screen makes password recovery easier. The password recovery process model is shown in the image below. To start the password reset process, users must provide the email addresses linked to their accounts. This feature guarantees a seamless user experience while improving security.

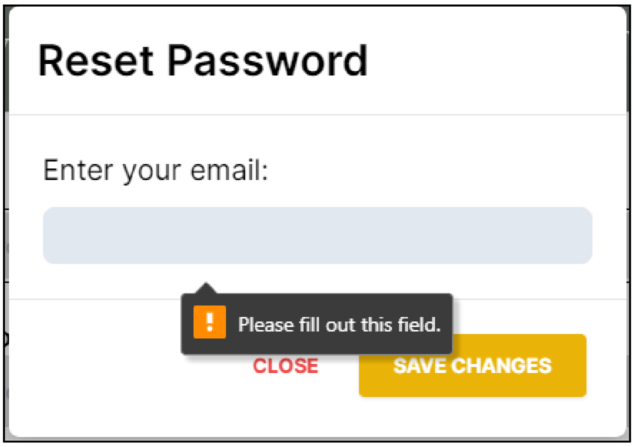

Fig 3. Forgot Password Modal:

The user will receive a confirmation email as soon as their email is submitted, allowing them to reset their password in the database.

B. Register Page

Shown below is a figure of our registration page, which can be accessed from the login page.

Fig 4. Registration Page of the Application

Users must provide their email addresses, first and last names, preferred passwords, and a confirmation of their selected password on this page. Users will be automatically taken to the login page upon completing the registration procedure, allowing them to access their newly formed account immediately.

C. Home Page

Users will be taken directly to the main page after logging in successfully. The interface of the main page is shown visually in the figure below.

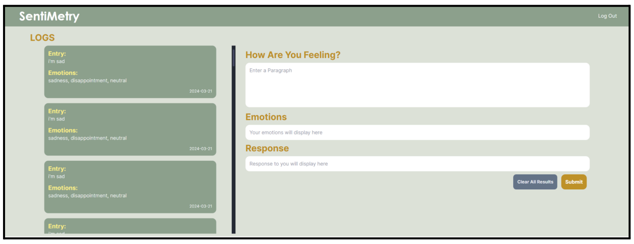

Fig 5. Home Page of the Application

On the right-hand side of the page, users are invited to express their current emotional state and journal their thoughts or any desired text. After submission, the feelings and replies will be displayed underneath the journal entry, providing users with information and comments.

Users can view their archived logs on the left-hand side, arranged chronologically from the newest to the oldest entry, with the most recent log appearing at the top. Every entry is displayed as a rectangle that holds the journal entry, the emotions selected by the algorithm, and the appropriate response. This design makes it simple for users to get and study previous logs for reference and introspection.

D. Emotion Determined

As seen in the figure below, the determined emotions of the user are presented based on the user's current answer to how they are feeling.

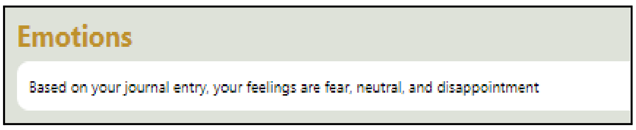

Fig 6. Determined Emotions of the User

EmoRoBERTa, Logistic, and Keras are three advanced models used to compute the user's emotions in a complex process. These models are intended to accurately estimate the user's emotional state by analyzing various input elements, from textual content to behavioral patterns.

The algorithm aggregates the scores associated with various emotions by merging the outputs of these models and adding them together to find the top three highest scores. This all-encompassing method guarantees a thorough and precise evaluation of the user's emotional state, allowing the system to react appropriately by providing the necessary support or assistance.

E. Response

The figure below shows the response or feedback generated based on the text entry given by the user.

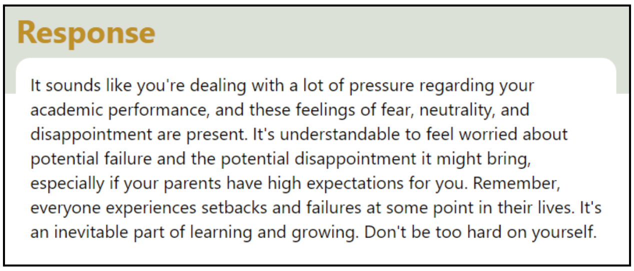

Fig 7. Response for the User

In addition to incorporating the user's text input and the identified emotions, the Mistral-powered answer field offers thoughtfully constructed feedback customized to the user's emotional state, offering support. A more personal connection is built with the user by addressing them by name. This makes the response more meaningful to the user and encourages empathy and understanding throughout the engagement.

F. History Page

As shown in the figure, the user can view their past logs, complete with their text entry, determined emotions, and feedback/response.

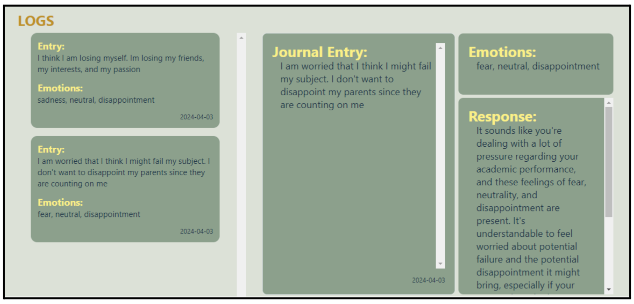

Fig 8. History Page

Access to previous logs allows users to review and be reminded of their emotional states over time, offering insightful analysis and a self-reflection tool. With the help of this tool, users may better understand the patterns, triggers, and swings in their emotions, enabling them to create coping mechanisms and better manage Their emotions. The approach improves emotional well-being, personal growth, and development by encouraging self-awareness and contemplation.

G. User Testing

In testing the application, we surveyed 21 users about their experience with the application, how they feel about it, and their suggestions and recommendations.

The list below contains the questions used in the survey to test the application on its users.

1.) How easy was it to navigate through Sentimetry's features and functionalities?

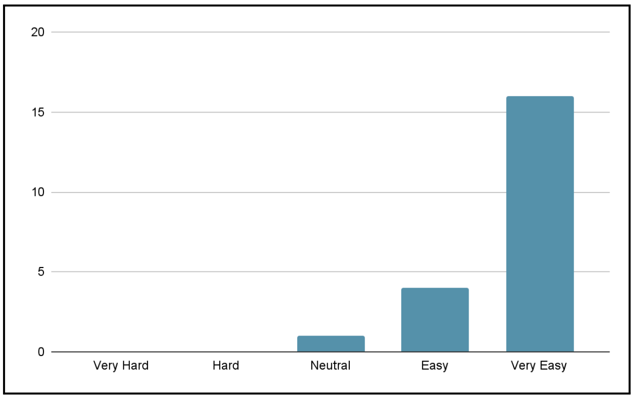

Fig 9. Results of How Users Find the Navigation of Sentimetry

Most participants, or 76.2%, reported finding Sentimetry's features and functionalities extremely user-friendly. The application's user-friendly interface, which incorporates interactive shapes and buttons, might be responsible for the high satisfaction rating. These characteristics enhance users' navigational pleasure by enabling smooth platform engagement. Sentimetry's user-friendly design features highlight their dedication to offering an easy-to-use and intuitive interface, increasing user satisfaction and engagement with the program.

2.) How accurately do you feel Sentimetry reflects your emotional state based on your journal entries?

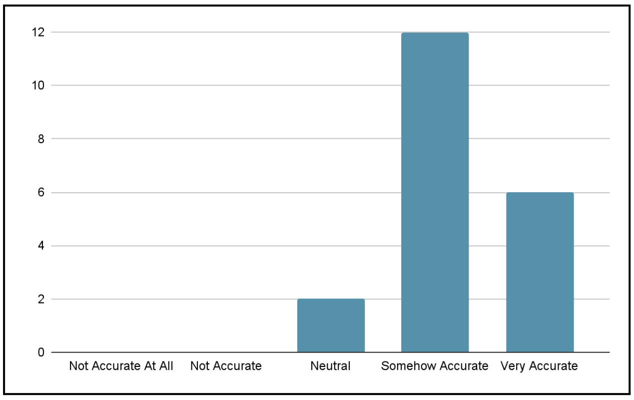

Fig 10. Result of How Users Find the Accuracy of Sentimetry in Determining Their Emotions

Based on the chart above, 10% answered very accurately, and 60% of the respondents answered that Sentimetry is likely accurate in determining the emotions of the text entry. The fact that everyone agrees strongly shows how much users believe Sentimetry can reliably identify and evaluate their emotions from journal entries. This resounding consensus validates the platform's competence in identifying emotions and strengthens its standing as a trustworthy resource for emotional self-awareness and assistance.

3.) How empathetic do you perceive Sentimetry's advice based on your emotions and journal content?

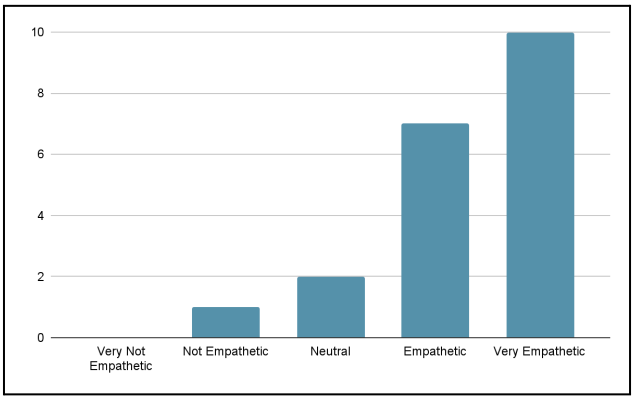

Fig 11. Results of How Empathetic SentiMetry is Based on the Experience of Users

Seventeen of the twenty-one people who participated in the study stated that they thought Sentimetry's advice was empathetic. This finding could be explained by the platform's use of customized replies produced by examining users' journal entries and using an advanced large language model. Through these technologies, Sentimetry can proficiently formulate tailored recommendations that connect with the complex emotional experiences of its customers, thus cultivating a sense of empathy in its counsel. These results highlight the platform's potential to communicate with users on a profoundly empathic level, improving their entire experience of receiving emotional assistance.

4.) How did you feel about the feedback provided by Sentimetry?

Responses to this question are short answers. User satisfaction with the feedback received is generally high, with users considering it accurate and helpful. Remarkably, one person conveyed deep gratitude and called the comments perceptive. They observed that it consistently could accurately identify their emotions, allowing them to understand their experiences more deeply. They further stressed how this realization has been beneficial in skillfully navigating a range of emotional states. These testimonials highlight how successfully Sentimetry works to help its users become more self-aware and emotionally healthy.

5.) What aspects of Sentimetry do you think could be improved?

Most user reviews indicate general agreement about how Sentimetry's color palette and overall appearance might be improved. A lively thematic presentation is something that many people express a desire for. In particular, one user expressed that they would rather allow voice postings than text entries and questioned the need for typing in modern journaling practices. They suggested including audio or visual input that could be easily transformed into text. Additionally, the user proposed investigating the feasibility of integrating sentiment analysis through audio or visual inputs.

H. Strengths

Senimetry includes personalized support through customized insights based on the users' emotional state, facilitated by AI sentiment analysis. This feature is what sets Sentimetry apart from other traditional online diaries, as it provides users with assistance and guidance during challenging times, which is particularly beneficial to those with mental health issues. It acts as a sympathetic virtual companion by offering comfort to users when navigating their emotional landscapes.

I. Limitations

Sentimetry also faces limitations such as privacy concerns stemming from using AI-driven sentiment analysis and potential dependence on technology. Additionally, it lacks the depth of human interaction in traditional therapy and counseling settings and could pose accessibility challenges for users with limited technological capabilities and internet access. In terms of language, Sentimetry currently only supports English. Furthermore, because Sentimetry only accepts text-based inputs, it has trouble identifying sarcasm. Because sarcasm depends on tone, it is frequently difficult to accurately identify using textual analysis alone. This restriction highlights how challenging it is to replicate subtle human communication using AI-powered sentiment analysis technologies such as Sentimetry.

V. CONCLUSIONS

The results of 21 participants for user testing showed that SentiMetry has potential as a tool for emotional well-being and self-awareness. Users found the design appealing and the features easy to use, which is important for user satisfaction and engagement. Users also felt comfortable sharing their journal entries for analysis, which shows that SentiMetry is a safe and supportive environment for introspection. SentiMetry uses AI to analyze emotions and provide personalized feedback, which users find accurate and empathetic. They also recognized the value of the insights and feedback provided by SentiMetry in managing daily challenges and emotional well-being. Although users suggested improvements, such as visual presentation and alternative input methods, most found SentiMetry impactful and would recommend it to others. These findings show that SentiMetry positively affects users' emotional health and can be a valuable resource for promoting self-awareness and emotional resilience.

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