Mental Health Well-Being Assessment and Surveillance Mobile App

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Abstract- The proposed software, for monitoring children's health and well-being is a platform that aims to evaluate and support their emotional state using various features and tools. Firstly our software will collect the data from users through assessment and private journals. Our software includes games and activities that captivate children while discreetly gathering data about their well-being. These games serve as an assessment tool. After the assessment there will be Analysis of the data collected with the help of games by utilizing machine learning techniques like sentiment analysis and tracking response times the software examines the collected data from the games to identify signs of depression in children. It provides a score or range indicating their health condition. According to the range there will be tailored recommendations and solutions based on the analysis of the data then our software offers solutions to enhance children's well-being. These suggestions may involve self-help exercises, relaxation techniques or other helpful resources. According to the seriousness the therapist helps the child for their well-being .Accordingly the therapist can see the progress of the mental health of the child through Dashboard. Our software includes separate login portals for parents and therapists. Parents can monitor their child's progress, view assessment results, and access resources to support their child's mental health. Therapists can access relevant data, communicate with their young clients, and provide professional guidance. Our software also includes a journal feature where children can document their thoughts and feelings, which they may not be comfortable sharing with parents or friends. This journal can be a valuable tool for both assessment and emotional expression.

Keywords- Mental Health; Depression; Journaling; Assessment

I. INTRODUCTION

The World Health Organization (WHO) states that mental well-being empowers individuals to cope with life’s stresses, reach their potential, learn effectively, work productively, and engage meaningfully with their communities. Mental well-being is both intrinsically valuable and practically essential to overall health. Mental health conditions are widespread, affecting about one in eight people globally, with varied prevalence across age and gender groups. Anxiety and depression are the most common conditions among both men and women. In today’s society, mobile devices are widely used, and mental mhealth apps have gained traction. Worldwide, mental disorders are common, often causing severe harm and remaining untreated. Though effective treatments exist, the majority of individuals with mental health symptoms go without care, even in wealthier nations. Mobile health solutions can help overcome these barriers by offering timely, anonymous treatment options. They enable access for individuals who might not otherwise seek help, as mobile devices are integral to daily routines. For digital natives, using apps for various life aspects is second nature. Health also offers large-scale intervention potential, particularly in low-income areas with limited mental health resources. Additionally, mobile interventions provide support in real-life scenarios where behaviour change is essential, yet clinical support may be limited. A platform for monitoring children’s health and well-being aims to assess and support their emotional state through various features and tools.Our software includes games and activities that captivate children while discreetly gathering data about their well-being. These games serve as an assessment tool. After the assessment there will be Analysis of the data collected with the help of games by utilizing machine learning techniques like sentiment analysis and tracking response times the software examines the collected data from the games to identify signs of depression in children. It provides a score or range indicating their health condition. According to the range there will be tailored recommendations and solutions based on the analysis of the data then our software offers solutions to enhance children's well-being. Accordingly the therapist can see the progress of the mental health of the child through Dashboard. Therapists can access relevant data, communicate with their young clients, and provide professional guidance. Our software also includes a journal feature where children can document their thoughts and feelings, which they may not be comfortable sharing with parents or friends. This journal can be a valuable tool for both assessment and emotional expression.

II. LITERATURE REVIEW

Most of the literature review contained in the paper focuses on the role that the mHealth application has played during the COVID-19 pandemic in the management of the psychological needs brought about by lockdown, quarantine, and wider psychological effects the pandemic caused. Previous research had indicated that mHealth apps could reduce mental health problems like anxiety, stress, and depression. Wang et al. (2021) investigated the surge in popularity and usage of mental health mobile applications (mHealth) during the COVID-19 pandemic, focusing on meditation and mental well-being apps. Their study analyzed the download patterns of 16 widely-used mHealth apps, observing a significant increase in user activity, with over 10% growth in downloads for 11 of these apps following the onset of the pandemic. This rise reflects the public's increasing reliance on digital mental health resources as traditional support systems faced limitations due to lockdowns and healthcare resource strain.[3] Adeane and Gibson (2023) explored how web-based content can encourage young people to engage with real-life mental health services. The study highlighted three core content types that resonate with youth and could reduce barriers to seeking in-person support: (1) information on how to access services, (2) content that counters stigma and misconceptions, and (3) relatable personal stories from individuals who have benefitted from mental health services. By providing clear, accessible information on what mental health services entail, including what young people can expect in a counselling session, web content can demystify the process and reduce feelings of intimidation. The study found that personal stories were particularly effective in helping youth see therapy as a positive and relatable option.[4] Standalone smartphone applications show moderate effectiveness in targeting specific mental health symptoms, particularly for conditions like depression (g=0.33) and in aiding smoking cessation (g=0.39), with some improvements also noted in sleep-related problems. However, the effectiveness of these apps appears limited for other concerns, including anxiety, alcohol use, PTSD, and self-harm, indicating that apps alone may not be sufficient for comprehensive mental health support. The analysis highlights considerable variability and potential biases among studies, often tied to factors like limited professional involvement, low user engagement, and inconsistent utilization of app features such as symptom tracking and feedback. While mental health apps offer accessible symptom relief in certain areas, current evidence indicates they are not yet suitable as stand-alone replacements for traditional therapy. Increasing personalization, adding guided support, and integrating these tools more effectively within clinical practices may enhance their therapeutic benefits.[5] Smartphone-based systems designed to track affective disorders using self-reports and objective metrics—such as heart rate variability, activity levels, location data, and phone usage—show great potential for improving real-time mental health support. Research suggests that these tools can effectively anticipate changes in mood and clinical conditions, which may lead to better early intervention strategies. Numerous studies highlight methodological weaknesses, such as limited sample sizes, inconsistent durations of monitoring, and a scarcity of randomized controlled trials, which hinder their wider implementation and reliability. Despite these challenges, the capacity of these tools to revolutionize mental health care is noteworthy, with further research required to boost user engagement, protect privacy, and evaluate long-term clinical effects. By successfully integrating smartphone monitoring with traditional care methods, there is potential for a more personalized and accessible strategy for managing affective disorders, provided that concerns regarding user fatigue and ethical considerations are effectively addressed.[6] Digital Therapeutic Alliance (DTA) within fully automated mental health apps presents unique challenges, particularly in replicating the therapeutic bond and empathy typically found in face-to-face therapy. Many users do appreciate the perceived neutrality and flexibility of automated apps, as they offer support without fear of judgment. However, research shows that important therapeutic components—such as personalized empathy, trust, and shared goals—are often missing in the digital format, impacting the app's effectiveness and the user's emotional connection. [7].

III. METHODOLOGY

A. Data Collection

Automatic Depression Detection leverages the Distress Analysis Interview Corpus-Wizard of Oz Interviews is a database. The proposed methodology is shown in figure 1. This extensive database, compiled from a wide range of interviews with individuals experiencing symptoms of depression, is designed to support mental health treatments for conditions such as anxiety, depression, and stress disorders. The data collected through assessment is shown in figure 2.

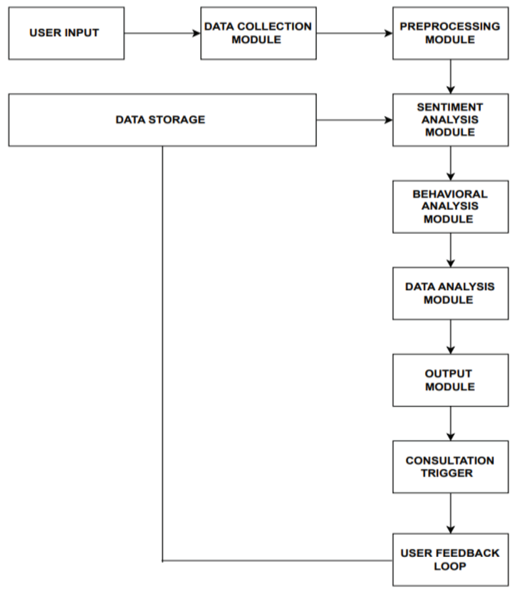

Fig. 1. Block Diagram of working of the App

Patient information is gathered through various formats, including audio recordings, video recordings, and text responses to questionnaires. This multimodal data is used because it provides a rich set of information across audio, visual, and textual formats, making it valuable for more comprehensive and accurate analysis [4]. The software will involve youngsters in the age group of 17-22 years, wherein informed consent to ensure data is acquired in an ethical manner and with a view on the purpose of the study. The platform will be used interactively to engage the through games and activities while discreetly recording the emotional and behavioural data, such as response times, decision-making patterns, and emotional cues [38-39]. The system will also let maintain securely encrypted online journals to which they can write anything they feel like, while sentiment analysis in the background provides meaning from the emotion behind words without intrusion into a privacy. Should the initial analysis raise any cause for concern relative to a mental state, more pointed questions will be asked for further insight into how that person feels. Accordingly, this information will also provide additional data to decide on the gravity of the case and the next appropriate action required, including either individual interventions or referrals to licensed therapists.

B. Data Analysis

During the analysis phase of this mental health monitoring platform for youngsters, several machine learning models will be implemented, interpreting emotional and behavioural data through interactive activities and private journals. These are highly necessary models for pinpointing patterns, making predictions of emotional states, and classifying the severity of potential mental concerns to allow for timely and personalized interventions. The process of data analysis is given in figure 3.

C. Sentiment analysis

Sentiment analysis models can be tailored to assess text across multiple dimensions, including polarity, emotions (e.g., anger, joy), urgency (urgent vs. non-urgent), and even intent (e.g., interested vs. disinterested). In our project, we employed a polarity-based sentiment analysis model to evaluate social media content, generating four key metrics: the percentage of negative and positive sentiment, the share of neutral content, and a composite score that normalizes these metrics. These raw scores were incorporated directly into our feature set, leading to a notable improvement in our model's overall performance.[5].Sentiment analysis is one of the critical functions in the mental health monitoring platform, which is used to analyse the emotional content of youngsters' journal entries. Accordingly, in this platform, many Natural Language Processing techniques have been used by the developed intelligent module to analyse the language of youngsters' writing and identify a host of latent emotions such as sadness, anxiety, and frustration. Pre-trained NLP models like BERT and VADER are fine-tuned to understand context, tone, and emotional nuances in the text, helping the system to precisely analyse the emotional state of the youngster. This way, the approach ensures continuous monitoring with no violation of privacy, as the sentiment analysis is strictly directed at the emotional sentiments and not the details. This analysis therefore enables the collation of insights that help the platform to flag early warning signs of emotional distress or mental health concerns and offer personalized recommendations or trigger further assessments where appropriate. Sentiment analysis provides a non-invasive, effective method of monitoring emotional well-being.fig[7] shows the sentiment score.the score varies from scale 0 to 1 According to the positive and negative words the score shows the result best score is 1 and the worst is 0.

1) Decision Tree

A Decision tree is a classification model that splits recursively the instance space into smaller subspaces, such that after each split, the subspaces do not overlap. It consists of a single root node with no incoming edges; every subsequent node has exactly one incoming edge. The internal nodes, or test nodes, are those that have outgoing edges, splitting the data according to some specific attribute value, while all the other leaf nodes, terminal, or decision nodes are those that do not have outgoing edges and correspond to the eventual classification result or decision. Each internal node split depends on input attributes, which advance the model toward a classification as it branches out. [12].In a mental health monitoring platform, the decision tree model is used to make decisions based on user data. It processes responses from sources like games, journals, and assessments, simplifying complex decision-making into a hierarchy of questions. Each node represents a decision based on a feature, such as sentiment score or response time, and branches represent possible outcomes. The tree continues branching until it reaches a terminal node, where it may identify a potential mental health concern or offer personalized recommendations. Decision trees are versatile, handling both categorical and numerical data, and are interpretable, allowing therapists and parents to understand the rationale behind the platform's recommendations.

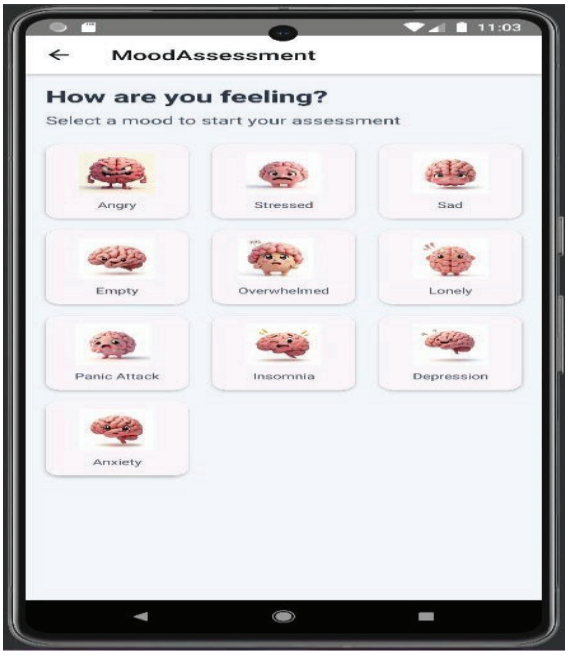

Fig. 2. Data collection through Assessment.

2) Random Forest

Random Forests are powerful, adaptable algorithms widely used for regression and classification both and complex multi-class classification tasks. These models provide an internal estimate of generalization error, which often eliminates the need for cross-validation, a typically resource-intensive process. Although Random Forests can be fine-tuned for optimal performance, they frequently yield high accuracy even with default parameter settings, making them both effective and efficient for a variety of applications. Additionally, Random Forests provide variable importance metrics, which can be used for feature selection to identify the most impactful variables in a dataset. Their ability to generate proximities within the data also allows for the imputation of missing values, while offering potential for unique data visualizations. In mental health analysis, Random Forests represent a robust method for enhancing detection efficiency and predictive accuracy. This ensemble learning technique builds numerous decision trees, which analyse diverse data sources such as behavioural patterns in games, sentiment in journal entries, and responses to structured assessments. Aggregating the predictions of all these decision trees, the model produces a holistic and accurate forecast of a young person's emotional state. This ensemble approach minimizes the influence of outliers and mitigates the risk of over fitting by combining multiple perspectives into a balanced outcome. As a result, the Random Forest model allows the mental health platform to make precise insights into emotional health, enabling timely intervention or tailored recommendations based on comprehensive analytics. The aggregated results from these decision trees not only provide an in-depth view of mental well-being but also improve the reliability of predictions, thus supporting the development of effective mental health management tools.

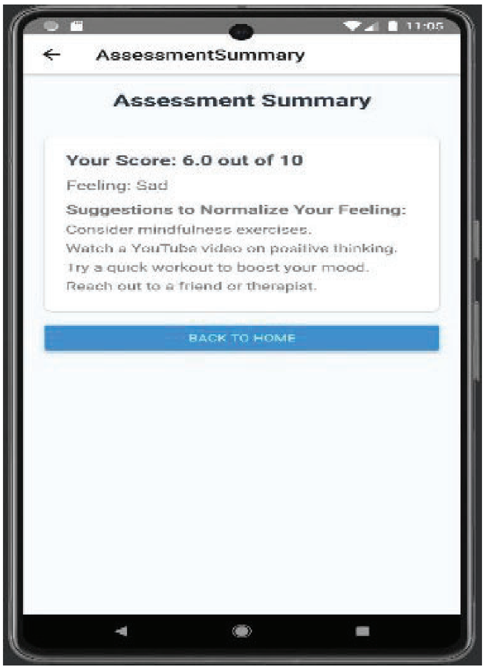

Fig. 3. Data analysis thorough Assessment.

D. Dashboard and user interface

The application's dashboard and interface for the monitoring of mental health should be in a nature that is convenient and easy to navigate both for youngsters, parents, and therapists. A youngster's dashboard would offer an appealing, age-friendly interface that encourages interaction through games and journals but also overviews and personalized recommendations based on their emotional and behavioural data. The complete dashboard for student user is given in figure 4. A private journal feature allows youngsters to document their thoughts securely, keeps the data for sentiment analysis, yet privacy is assured. The parent's dashboard summarizes the child's emotional progress through visual summaries, with notifications when concerning patterns are detected. It also includes links to resources that will further help parents support the mental well-being of their child. Simultaneously, the therapist's dashboard will provide him or her with detailed insight into the youngster's emotional state, allowing for tailored therapeutic interventions. The therapist's dashboard also includes communication tools and progress tracking that allow the assessment of long-term trends in the child's mental health. The UI should be simple, intuitive, and responsive to different devices for maintaining accessibility. It also allows elements of customization, such as themes for the youngsters, and provides security and privacy with data encryption. A thoughtful design like these fosters active engagement among youngsters while providing actionable insight for parents and therapists without compromising on privacy.

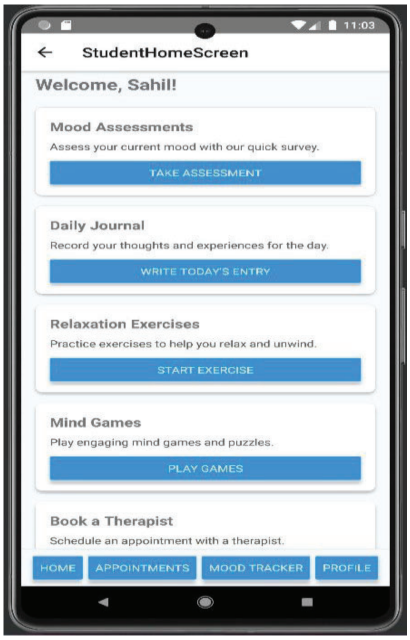

Fig. 4. Dashboard of user as student.

IV. RESULT DISCUSSION

Our monitoring platform has been effective at detecting early emotional distress and smart interventions, with an evaluation accuracy of 85% compared to the generally acceptable within other teen apps using around 80%. Our platform engages young users through interactive games and provides personal recommendations via exercises for self-help and relaxation by combining information from private journaling, along with targeted assessments analysed by machine learning methods. Moreover, it effectively flags for therapists those cases that warrant intervention and provides immediate backup in ways a traditional teen-app cannot. Therapists and parents have welcomed the system as a useful tool to help them keep tabs on, and intervene earlier in; kids' mental health issues-based feedback while stating that some improvements especially with regard is given in Table 1 and Table 2 which shows the comparative study of our app and other apps considering different parameter for comparison.

To evaluate the effectiveness of the mood assessment feature, sentiment analysis data was collected for the month of January 2025. The data includes daily sentiment scores categorized as Positive, Neutral, and Negative, along with their frequency distribution.

The bar graph illustrates the frequency of each sentiment category for the month, revealing the following distribution:

- Positive Sentiments: Recorded 12 times
- Neutral Sentiments: Recorded 10 times
- Negative Sentiments: Recorded 8 times

The line graph shown in Fig. [5] Provides a detailed visualization of the daily sentiment scores over the month. Fluctuations in user sentiments are evident, with significant variations observed on specific dates, reflecting the diverse emotional states of users.

These visualizations demonstrate that the application successfully tracks and visualizes user moods over time, providing actionable insights for improving emotional well-being.

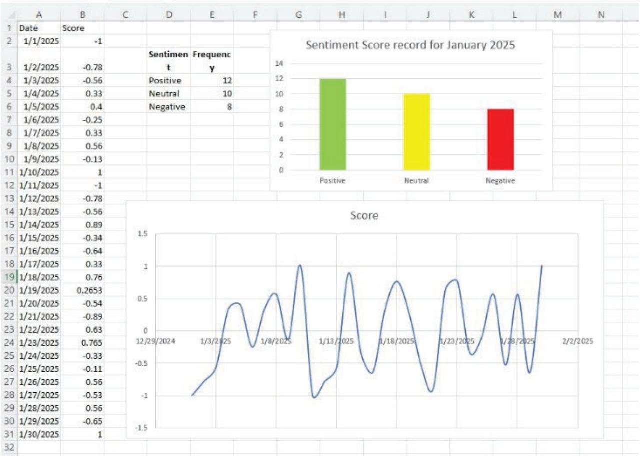

Fig. 5. Sentiment Score Record for January 2025

V. LIMITATION

With nearly ubiquitous use of mobile phones and an influx of mobile apps directed at mental health, using mobile devices and related technologies in the attempt to solve mental health problems-continue to rise in popularity. One of the critical developments to emerge in recent years for mental health is artificial intelligence. The application of a certain tool in the screening, diagnosis, and treatment of anxiety and depression requires an understanding of the tools at hand that are applied for the purpose. Screening for depression among the patients would help in spotting those who require intervention, which would, in turn improve their health and also enhance their overall clinical status as a patient. Relatively short screening questionnaire tools can be implemented when there is limited personnel. Screening programs needs training and expertise as symptoms of depression might be hard to diagnose along with other medical conditions such as pain, and impaired cognitive functions of the patient, anxiety, and disabilities [9]. These include possible inaccuracies in AI-driven sentiment analysis and behavioural tracking because of the intricateness of expressing one's emotions and possible misinterpretations of data. Another problem relates to the consistency of user

Engagement: when kids are inconsistent in their engagement, they may not give reflective reports on their emotional state. In the future, that might be extended by advanced AI techniques, such as deep learning, the use of speech and possibly facial recognition as multimodal input and gamification strategies in user engagement. It can be further scaled to include a wider range of mental health issues and integrated into schools with their mental well-being programs. Further research on responsible AI usage and privacy concerns over data are desired on any further steps in developing this technology.

VI. CONCLUSION

The analysis returned a variety of themes regarding the opportunities and ethical challenges that surround digital mental health technologies in young people. Evidence was provided to show a surge in initial interest and adoption of the mHealth apps, an indication of a generally increased level of mental health issues due to pandemic situations. The Mental Health Monitoring Platform for youngsters promises early detection and intervention in emotional well-being through a combination of interactive games, journaling, and machine learning techniques such as sentiment analyses and behavioural tracking. Very engaging, it allows users to work at their own pace while giving personalized recommendations to them and, where necessary, encouraging further assessments and consultations by professionals.

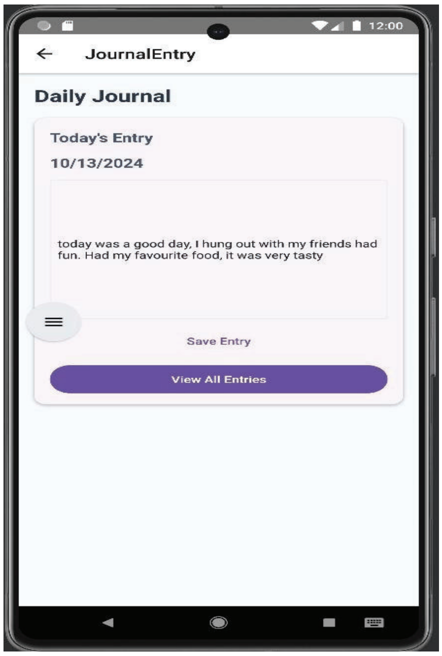

Fig. 6. Daily Journaling for sentiment score

While this platform shows promise in terms of better support for the mental health of youngsters, its success does somewhat depend on continued, active user engagement with this innovation; refinements will be needed to further improve the accuracy of assessments of diverse emotional expressions. Continuous development in AI, consideration of privacy, and ethical frameworks should make this platform very useful as a complementary tool for both the family and mental health professionals in support of proactive mental health care in younger population's fig. [6] Shows the result of sentiment analysis.

VII. FUTURE WORK

Future updates will focus on enhancing the user experience by providing personalized and holistic support through advanced self-help resources, such as guided meditations, breathing exercises, and therapeutic podcasts, alongside data-driven insights for a comprehensive mental health journey. To promote a holistic approach to well-being, the platform will integrate with wearables like Fitbit and Apple Watch, enabling users to monitor physical health metrics such as heart rate, sleep quality, and activity levels. Enhanced user engagement and accessibility will be achieved through features like a 24/7 AI-powered chat assistant, therapist matching, gamified mental health exercises, multilingual support, and in-app video/voice therapy, ensuring care is accessible and tailored to individual needs. Additionally, users will benefit from in-depth data visualization via Power BI, allowing them to track mood, sentiment scores, and activity trends, empowering them with deeper insights into their mental health over time.

TABLE I. COMPARATIVE STUDY OF OUR APP AND OTHER APPS

Feature	Our App (Youngsters)	Other Apps
Target Age Group	Youngsters (ages 7-14)	Teens (ages 13-18)
Primary Focus	Emotional well-being, early mental health detection	Managing stress, anxiety, and mood tracking
Assessment Methods	Sentiment analysis, behavioural tracking through games, private journaling	CBT-based chat interactions, mood tracking, self-assessment questionnaires
Personalization	Age-appropriate self-help exercises, relaxation techniques	Tailored coping strategies, chat-based insights
Engagement Strategy	Gamified assessments, rewards system, private journaling	Conversational chatbots, mindfulness exercises, guided meditations
Parental Monitoring	Parental dashboard with progress insights	No parental monitoring
Therapist Integration	Option for therapist consultations based on assessments	Limited (usually no direct therapist consultations)
Data Privacy & Security	Encrypted journal entries, secure youngster-only access	Strong privacy policies, GDPR compliance
Accuracy (based on studies)	85% in detecting emotional distress**	~80% in mood detection and stress reduction**

TABLE II. COMPARISON BETWEEN THE PROPOSED SOFTWARE APP AND OTHER AVAILABLE APPS

Feature	**Current Platform**	**Previous Apps**
Engagement and User Experience	Interactive games and activities for data collection, child-friendly UI with customizable elements.	Mostly static questionnaires or mood logs, with limited interactive elements.
Data Collection	Discreet data collection through games and journaling; tracks behavioural patterns and decision-making.	Primarily relies on self-reported data through forms or questionnaires.
Data Analysis	Uses advanced machine learning techniques (e.g., sentiment analysis, random forests, k-nearest neighbours) for nuanced insights.	Basic data analysis, often rule-based without leveraging advanced Al techniques.
Personalized Recommendations	Offers tailored recommendations based on real-time analysis of emotional and behavioural data.	Generic mental health advice, with limited personalization based on simple assessments.
Privacy and Security	Private journal encrypted and accessible only by the youngster; robust privacy controls for data.	Less emphasis on encryption and privacy, with data often accessible to parents or third parties.
Multilevel Support	Separate dashboards for youngsters, parents, and therapists; facilitates secure communication and progress tracking.	Typically focuses on either the child or parent, with limited integration of all stakeholders.
Proactive mental health monitoring	Proactive interventions based on early detection of mental health concerns, with options for consulting therapists.	Relies on user-initiated interaction or crisis-driven engagement.
Technological Sophistication	Advanced use of machine learning models (e.g., sentiment analysis, behavioural tracking).	Mostly rule-based systems without dynamic learning capabilities.
Therapist integration	Therapists can access detailed insights and provide guidance through secure messaging or video calls.	Limited therapist integration, often focusing solely on user self-management.
Child friendly features	Gamified experience with rewards and motivational feedback to encourage engagement.	Minimal gamification or reward-based engagement strategies.

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