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ADAPTIVE HYBRIDE AI SYSTEM FOR PREDICTING AND PREVENTING GLOBAL MENTAL HEALTH CRISES: REVIEW AND PROPOSED SOLUTION

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Abstract: There are increasing rates of mental health issues around the whole world, particularly with youth and also digital natives. In this review paper, I review Artificial Intelligence (AI) applications around tracking mental health status and propose a hybrid AI tool combining sentiment analysis from social media platforms (e.g. Twitter, Facebook, Instagram & others) with self-reported survey data to assess emotional risk in real-time. Current systems are often lacking personalization, flexibility, and also transparency. The proposed model attempts to fill these gaps using reinforcement learning and Explainable AI (XAI) to provide interpretable and adaptable support. It also allows multilingual data processing and ongoing learning based on user feedback. I discuss key methodologies, which include natural language processing (NLP), hybrid data fusion, and unique risk profiles. I highlight the current research limitations and introduce a scalable AI framework, I have designed to enable ethical, real-time, and user-centered mental health monitoring and intervention.

Index Terms - Mental Health, Human-Centered AI, Preventive Healthcare, Hybrid AI Architecture, Natural Language Processing (NLP), Explainable AI (XAI).

I. INTRODUCTION

Mental health disorders, such as anxiety, depression, and stress-related conditions, are rapidly becoming a global issue. The World Health Organization (2023), estimates that more than 970 million people worldwide live with mental disorders which make mental health a leading cause of disability and lost productivity. Mental health issues cause more than just emotional distress, they clearly have an impact on academic performance, job performance, interpersonal relationships, and life quality overall.

In recent years, with the rise of digital platforms, people are more willing to share their emotional state and feelings on various online platforms. This digital footprint, particularly on social media platforms, allows for valuable data on emotional trends and behavioural patterns (McCormick & Horvitz, 2018). Concurrently, advances in artificial intelligence (AI), with natural language processing (NLP) and machine learning (ML), have the capability to analyse this data to find early warning signs of mental distress (Rao et al., 2022).

Even though interest in AI-based mental health monitoring is increasing, existing systems have a number of issues. Many existing models are based on one data source, either a public social media post or private survey input, and do not take into account both perspectives. In addition, existing systems tend to be static and do not adapt to the users' changing behaviours and do not have an adaptive personal recommendation feature over time (Smith & Nguyen, 2023). Another major issue is the lack of explainable AI (XAI) since users need to trust the conclusions reached regarding their mental state, and it is difficult to trust a model without understanding how it reaches a conclusion (Chen et al., 2023).

To mitigate these limitations, this paper outlines a hybrid AI system that combines real-time social sentiment with structured survey data to provide an adaptive, explainable, and personalized approach to mental health prediction and prevention. The proposed system is fed user feedback in order to continue to learn and improve, and ensure that health recommendations are always accurate and personal to an individual user.

II. Literature Review:

Artificial Intelligence (AI) has made significant strides in mental health research given that it can process behavioural data at scale.

Smith et al. made use of classical ML models including SVM and Random Forest, on structured health survey data to identify anxiety and stress. Their models were accurate, but did not adapt nor learn how users behaved after deployment.

Rao et al. used sentiment analysis of X (formerly twitter) data for identifying users that could be at risk of depression. In fact, using LSTM improved sentiment recognition in context, but this system was one-dimensional, only included public text, and it did not have a mechanism for private feedback or personal feedback from digital behavioural engagements.

Nahum-Shani et al proposed the Just-In-Time Adaptive Intervention (JITAI) model which had the ability to dynamically prompt adaptive behaviour with the change in context. While this model was conceptually adaptive, it did not stipulate that emotional signals from digital behavioural interactions could not be included in risk profiling for emotional attention as indicated in the research.

Chen et al. put an important lens on Explainable Artificial Intelligence (XAI) in digital health systems, which indicate user trust and confidence support transparency. In their analysis, it was noted that black-box models, no matter how accurate, are unlikely to make it into the healthcare space unless the model can be reasonably interpretable by clinicians and senior care providers and even the end-users.

Yazdavar et al. created a BiLSTM-attention-based model based on Reddit forums, and aggregating emotional content and social networks. The study was new, but did not have any personalized learning pathways nor was able to learn and change with user actions over time.

McCormick and Horvitz observed social media activity and mood changes to infer emotional lability through users' digital traces. The model and data mining were based on traditional rules and were not adapted to machine learning.

Zanwar et al. created a multimodal AI system that included facial dimensions of emotion, EEG signals of emotion, and audio to also produce sentiment. Despite the very high accuracy of prediction, the model required proprietary and specific hardware which made it unsuitable for general-purpose mobile mental health interventions.

Zhang et al. argued for a hybrid system that used wearables for health data and text sentiment. The design is promising but did not show clear user-directed feedback loops, and did not contain explainable AI layers necessary for user engagement over time.

Saha et al. showed that Reddit sentiment can predict periodic spikes in use of counselling services at universities. Although they were successful in forecasting at the aggregate level, I do not believe their model could have been used to individualize mental health tracking or project an intervention, or provide personalized resources and support.

Classical machine learning models (SVM, Random Forests) applied to structured survey data can identify anxiety and stress from survey responses but do not allow for adaptability as they are deployed.

LSTM-based sentiment analysis of Twitter data yields better contexts for emotion detection, but they only have public text data to work with and do not assess private forms of feedback.

Just-In-Time Adaptive Interventions (JITAI) represent a dynamic mechanism for prompting users proactively when feeling distressed, however, they do not include digital behavioural signals when profiling risk.

Explainable AI is important for user trust and adoption (namely due to the need to minimize black-box models in healthcare environments).

BiLSTM-attention models applied to data on Reddit forums and emotional content and social networking can show patterns of emotional trajectory, but do not address learning pathways personalized for each user.

Rule-based social media emotion assessments allow for emotional lability inference but do not use machine learning to be flexible.

Multimodal emotion detection using facial analysis, EEG, and audio signals has a high accuracy rate, but it relies on proprietary hardware not usable in a mobile environment.

Hybrid wearables-text systems promise emotional monitoring, but lack clear feedback loops and explaining layers.

Reddit sentiment forecasting demonstrates that counselling is likely to spike at universities, but ultimately, it fails to provide individualized interventions.

AI-based chatbots and large language models (LLMs) in mental health typically do not run both public and private data streams at once, and so result in a lack of cultural inclusivity.

Real-time, AI-based support outside of normal face-to-face hours means there is greater potential enhanced self-regulation following emotional distress (severe) and it raises ethical and privacy dilemmas.

A hybridized mental health framework that combines digital mental health interventions, with human support that is responsive, increases both engagement and overall outcomes associated with mental health and distress.

AI-enabled chatbots (such as: Woebot, Wysa, Replika, Ginger, or Youper) offer 24/7 personalized user-support via chat, as well as mood tracking options.

Transformer-based embeddings (e.g., BERT, RoBERTa) are trained to respond to emotional subtleties in language, and improve detection of specific distress earlier in the messaging and therapy process (often where it arises).

By fusing together, a user's social media tasks, sentiment, survey data into a comprehensive and managed emotional profile provides better risk classifications.

The use of refreshable training via reinforcement learning in recommendation engines for interventions enhances an individual's long-term outcomes based on their feedback and stated needs.

Weighted fusion logic that refers to the process that fuses heterogeneous data sources in a comprehensive manner enhances risk prediction better than utilizing just one data source.

Imperfect normalized Likert-scale survey scores fused with TF-IDF vectorized textual features create a decidedly more robust hybrid "feature" space.

When feed-foreword fused input is utilized, utilizes a logistic regression on that fused input to classify mental health risks as low, moderate, or high.

Triggers for the emotional deterioration that associated first cognitive "Early prevention prompts" (journaling, meditation prompts) proved to be effective and no different when utilized first person.

As illustrated in the last two steps, using a streamlined front-end (e.g., a Streamlit website and a simple Google Forms survey) can lower hurdles for entering technical and/or non-technical user engagement.

Explainability modules help normative users interpret emotional cues as contributing broader emotional/mental states, thereby providing understanding and a sense of security/trust.

Transformers that balance numerous languages align more closely to cultural bias, so reducing the impact of any single cultural/linguistic bias in sentiment analysis.

Feedback loops that allow models to be trained incrementally and incrementally allow for personalization and improvements continues longitudinal performance.

Lightweight, hardware-agnostic AI in practice promotes scalability and opens the intervention to more users.

Built-in retrospection ethics in the log that allow for informed consent, and flags for emergency contacts, are critical to safe practice, particularly when working with users expensive emerging from emotionally charged scenarios.

Companion-style monitoring tools provide longer-term engagement thereby ongoing support, whereas one-off diagnostics, without ongoing support can yield no long-term resilience benefits.

AI-related diagnostic "e-triage" tools have been demonstrated to be nearly 93% accurate in detecting common mental disorders in diagnostic (clinical) pathways.

Voice analysis tools demonstrate the ability to detect depression and anxiety from a short recording of a "speech clip" that expands the potential modalities of screening.

AI can certainly promote companionship and thereby alleviate loneliness while increasing engagement, despite not replacing, however both require evident ethical limitations and safeguards.

More recent studies have also emphasized AI-enabled apps that use the power of chatbots and LLMs. However, most lack an integration of both 'public' (sentiment or posts in social media) and 'private' (chatbot logs, usage data, health app diaries) data streams. Many proposals have not met the need for dynamic, culturally inclusive, and explainable systems.

III. Research Gap Analysis:

Despite the existence of AI powered mental health prediction and interventions, the research gaps that persist will continue to decrease the efficiency and effectiveness of users of these systems. Compared to the advancement of computational processes and performances, the sparsity of effectiveness of “intelligent” mental health prediction systems is a modest effect on the landscape of AI mental health interpretation of data. Another limitation this AI systems experience is inflexibility. Most of the AI systems are *“non-adaptive”* meaning they do not respond to a user's experience and/or entry features resulting in a potential reduction in usability (Smith & Nguyen, 2023). Considering the inflexibility of AI in evaluation, there are serious limitations concerning the reliance on multiple sources of aggregated data. Content from social media sentiments and a user reporting via survey could yield integrated data on mental well-being for multiple participants at a similar time, but most AI models are not appropriately merging these differences in data type, which essentially weakens their effectiveness by only providing partial details (Rao et al., 2022).

Explainability (XAI) represents another challenge as it relates to user assurance in emotionally charged scenarios, like mental health. In these cases, establishing user trust is paramount, yet most of these models neglect to include any interpretable or understandable rationale behind their recommendations, creating reluctance for users to receive advice generated by an AI system (Chen et al., 2023). Furthermore, many AI applications entirely sample data retrospectively and don't allow for real-time representational feedback. This process is particularly troublesome in high-risk situations where immediate interaction can drive the user to positive or negative intervention (Nahum-Shani et al., 2021). Personalization is also extremely limited, and most models utilized rules-based guidance and generalized threshold decisions without considering an individual user's emotional history, baseline, or even real-time behavioural context (Yazdavar et al., 2020).

One more gap exists in the lack of prevention. Typically, if there is a risk of deterioration, a system operates after a risk is indicated, as opposed to providing prevention strategies to eliminate any chance of mental health declines in the first instance. Finally, in addition to not having a strong user interface and user experience, there are few systems that take user perceptions of their mental health into account (e.g. using interactive user interfaces or Streamlit/Google Forms to engage with one's own mental health data).

The *cultural and linguistic bias* remains, with most emotion detection models working predominantly on English data and ignoring ways of expressing emotional meaning that are based on regional languages, or non-verbal expressions that participants in various cultures might recognize (Liu et al., 2022). There are very few evaluative processes in place to evaluate whether the recommendations made by the system made any impactful changes to users' emotional cases, and without any evaluation process, feedback loops are not guaranteed (Shu, 2021). Lastly, although multimodal models based on EEG, facial expressions or voice input may offer potential, technical overheads typically erode user interest in sustaining use (Zanwar et al., 2022).

A clear oversight of ethical issues exists for what constitutes "care". Informed consent, active and passive user safety protocols, or emergency response logic surrounding users who are in acute emotional episodes are often insufficient. Evaluation is also short-lived. Most models test user experience for a few days and do not support users over the long-term emotional wellness trajectory, which is a vital component of resiliency and sustainability for mental health.

IV. Methods:

Proposed Solution:

This study will provide a solution to the pressing research gaps in existing literature by offering a hybrid, adaptive, and explainable AI system that recognizes and leverages emotional sentiment analysis from available public social media (for example X) and private, self-reported survey responses. The following solutions were designed to address the specific shortcomings of the identified approaches:

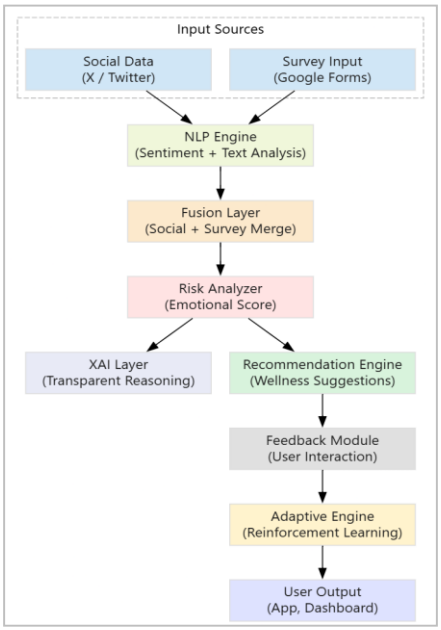


Figure 1.A: Sample System Architecture Diagram

1. Adaptive Learning that Leverages Reinforcement Feedback

The model (Figure: 1.A) uses reinforcement learning to mature based on user feedback over time. As users respond to feedback on their suggestions or emotional support requested and received, the AI changes its risk assessment and recommendations.

2. Hybrid Data Fusion

We will use self-reported survey data and sentiment signals from social media (Figure: 1.A) to build a more comprehensive emotional profile for each individual. The self-reported surveys and social media data can provide insight from two layers that can ensure better accuracy and context.

3. Explainable AI (XAI) Layer

To improve transparency and trustworthiness, our system includes explainability modules (Figure:1.B) that can show users which emotional cues, words, or trends triggered their certain risk alert. To help users understand the "why" behind each recommendation. Picture in bellow.

Figure 1.B: XAI Layer Explainer Diagram

4. Real-Time Interaction Engine

The architecture allows for real-time emotional state risk detection and intervention, providing timely recommendations throughout emotional low points (stress spikes or depressive signals).

5. Personalized Risk Profiling

Rather than generic thresholds, the system learns a personalized emotional baseline for each user and interprets risk detection within their prior behavior and states.

6. Early Prevention Triggers

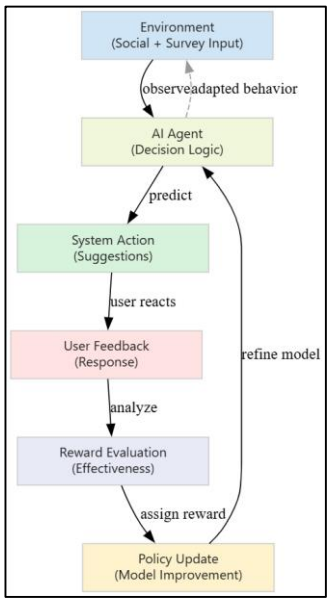
The model has the capability to go beyond detection by predicting emotional deterioration in the future and, more importantly, provide early prevention suggestions, such as journaling, meditation, or making a call to peers.

7. Easy to Use Frontend (Streamlit + Google Forms)

The system is offered as a lightweight frontend in Streamlit, with survey input via Google Forms, effectively minimizing the technical barrier and allowing non-technical users to interact with ways to learn.

8. Support for Multilingual Sentiment

In addition, the model could easily be expanded to utilize multilingual transformer-based embeddings to support users in diverse linguistic and cultural contexts, as well as broaden the reduction of bias and increase opportunities for inclusivity.



9. Feedback Loop Outcome Monitoring

The system asks users for feedback about whether the recommendation was helpful after each recommendation event (Figure: 1.C); the foundation of a feedback loop for modifying and edging the model's performance and tracking emotional recovery.

10. Lightweight, Scalable Design

In this model, there are no hardware dependencies related to the deployment and use of the app. This is different to all alternatives that have had EEG or facial recognition-based systems.

11. Built-In Ethical Logic and Consent

The system has built-in ethical logic from start to finish, including informed consent forms, emergency alert flags, and data-safe protocols in case psychological trauma emerges. We consciously considered user autonomy, psychological safety and accepting consent.

12. Support Framework for a Well-Being Relationship

The system is designed as a monitoring tool with respect to users and their emotional state over time, not just a one-off diagnostic tool. Rather, it aims to support users as a trusted companion that can help them with the ebb and flow of life.

V. Methodologies:

Component	Description
Data Collection	• **Social media:** Twitter posts and Reddit threads containing mental health-related keywords. • **Surveys:** Google Form-based self-assessment tools for stress, anxiety, and burnout. • **Behavioural Metrics:** Passive data such as screen time or app usage (optional module).
Data Processing & Analysis	• **Text Preprocessing:** Tokenization, stop-word removal, lemmatization. • **Sentiment Analysis:** NLP models like VADER and BERT for polarity and emotion scoring. • **Survey Scoring:** Normalized stress/anxiety scores using Likert scale metrics.
Hybrid Model Design	• Fusion of emotional (social media), cognitive (survey), and behavioural (passive) data. • Weighted fusion logic based on user profile. • Risk classification using Random Forest or XGBoost.
Adaptive Feedback Loop	• Personalized recommendations based on historical data. • Feedback collected on whether user found suggestions helpful. • Reinforcement learning updates recommendation engine.
Explainable AI (XAI) Layer	• Displays reasons for prediction and action (e.g., "High stress due to recurring negative language + 9/10 anxiety score").
Tools:	Python (Scikit-learn, Transformers, Pandas), Streamlit, Google Forms, Matplotlib.

Table: 1.A

Tool	Purpose in Project
Scikit-learn	Traditional ML model training (classification)
Transformers	Sentiment/emotion detection from social media text
Pandas	Data handling and preprocessing
Streamlit	Web-based frontend for user interaction
Google Forms	Survey data collection from users
Matplotlib	Graphical output of predictions, trends, and outcomes

Table: 1.B

The proposed framework combines data collection, preprocessing, sentiment analysis, classification, recommendation generation, and reinforcement learning.

Data Collection & Preprocessing *(Core Concept Code)*:

```python
import tweepy
import pandas as pd
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
import re

# Data collection from social media (e.g., X/Twitter)
def collect_social_media_data(api_key, api_secret, access_token, access_secret, query="mental health", max_tweets=10):
    try:
        auth = tweepy.OAuthHandler(api_key, api_secret)
        auth.set_access_token(access_token, access_secret)
        api = tweepy.API(auth)
        tweets = api.search_tweets(q=query, count=max_tweets, lang="en")
        return pd.DataFrame([t.text for t in tweets], columns=["text"])
    except Exception as e:
        print(f"Error collecting social media data: {e}")
        return pd.DataFrame()

# Preprocessing for social media and survey data
def preprocess_text(text):
    try:
        # Remove URLs, special characters, and convert to lowercase
        text = re.sub(r"http\S+|www\S+|[^a-zA-Z\s]", "", text.lower())
        # Tokenize and remove stopwords
        tokens = word_tokenize(text)
        stop_words = set(stopwords.words("english"))
        tokens = [t for t in tokens if t not in stop_words]
        return " ".join(tokens)
    except Exception as e:
        print(f"Error preprocessing text: {e}")
        return text
# Example usage
if __name__ == "__main__":
    # Replace with actual API credentials
    social_data = collect_social_media_data("your_api_key", "your_api_secret", "your_access_token", "your_access_secret")
    # Example survey data
    survey_data = pd.DataFrame({"text": ["I'm feeling stressed", "I can't sleep"]})
    # Preprocess both
    social_data["cleaned_text"] = social_data["text"].apply(preprocess_text)
    survey_data["cleaned_text"] = survey_data["text"].apply(preprocess_text)
    print("Social Media Data:\n", social_data[["cleaned_text"]])
    print("Survey Data:\n", survey_data[["cleaned_text"]])
```

Figure 2.A: Data Collection & Preprocessing

This module (displayed in Figure 2.A) conducts the all-important first phase, data collection and preprocessing, for the hybrid AI operating as a multi-modal input system that integrates data from social media and surveys. The social media data, which can include posts from X or Reddit that have mental health keywords, are collected by implementing the tweepy library and ensuring real-time emotional signals are accessed. Survey data, via google forms, gather a self-reported measure of stress or anxiety. In this module the collected data will be preprocessed to clean text to remove, URLs, special characters, and stopwords, followed by the tokenization of the data using NLTK. The clean social media and survey data is transformed by generating structured feature sets structured for downstream sentiment analysis and risk classification applications. The error handling and debugging processes support the reliability and robustness of the processes involved in this module and the overall system goal of scalable, real-time monitoring of mental health.

Sentiment Analysis Using Transformers *(Core Concept Code)*:

```python
from transformers import pipeline
from nltk.tokenize import word_tokenize
import nltk
nltk.download("punkt")

# Sentiment analysis using a Twitter-optimized model
def analyze_sentiment(text):
    try:
        # Initialize Hugging Face pipeline with RoBERTa for social media
        sentiment_analyzer = pipeline("sentiment-analysis", model="cardiffnlp/twitter-roberta-base-sentiment")
        # Tokenize for preprocessing
        tokens = word_tokenize(text.lower())
        result = sentiment_analyzer(text)
        return {"label": result[0]["label"], "score": result[0]["score"]}
    except Exception as e:
        print(f"Error in sentiment analysis: {e}")
        return {"label": "neutral", "score": 0.0}

# Example usage
if __name__ == "__main__":
    text = "I'm feeling overwhelmed and can't sleep."
    result = analyze_sentiment(text)
    print(f"Sentiment: {result['label']}, Confidence: {result['score']:.2f}")
```

Figure 2.B: Sentiment Analysis Using Transformers

The sentiment analysis component (shown in figure 2.B) uses a RoBERTa model from Hugging Face optimized for Twitter to classify social media and survey text as positive, negative, or neutral, which can detect subtle cues of emotion that may be useful for identifying distress early on. The text is tokenized using NLTK to improve the quality of the input to the model using natural language processing (NLP) techniques. The result is a sentiment label and a confidence score that will input into the data fusion layer of the system for determining risk. The system has multiple fallbacks to protect against errors during sentiment analysis, which reinforces the vision for the system as a safe, thorough, and automated methodology for accurately assessing and tracking the emotional state of individuals as part of a comprehensive assessment for predicting mental health.

Mental Health Risk Classification *(Core Concept Code):*

```python
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression
import pandas as pd
import numpy as np

# Combine social media and survey data for risk classification
def classify_risk(social_texts, survey_scores):
    try:
        # Vectorize social media text
        vectorizer = TfidfVectorizer(max_features=1000)
        social_vec = vectorizer.fit_transform(social_texts)
        # Combine with survey scores (normalized 0-10 scale)
        survey_vec = np.array(survey_scores).reshape(-1, 1) / 10.0
        combined_features = np.hstack((social_vec.toarray(), survey_vec))
        # Train model (example data)
        X_train = combined_features
        y_train = ["high", "moderate"]  # Example labels
        model = LogisticRegression()
        model.fit(X_train, y_train)
        # Predict risk
        predicted_risk = model.predict(combined_features)
        return predicted_risk[0]
    except Exception as e:
        print(f"Error in risk classification: {e}")
        return "low"

# Example usage
if __name__ == "__main__":
    social_texts = ["I'm stressed", "Feeling empty"]
    survey_scores = [8, 6]  # Example survey scores (0-10)
    risk = classify_risk(social_texts, survey_scores)
    print(f"Predicted risk level: {risk}")
```

Figure 2.C: Mental Health Risk Classification

The risk classification module (Figure 2.C) combines social media and survey-based data, focusing on predicting a person's level of mental health risk (low, moderate, high). Social media text data is vectorized using TF-IDF, while survey values (i.e. stress values on a 0-10 scale) are normalized. Both of these data sources are combined through a weighted fusion to create an emotional profile of the individual. A logistic regression model is then trained on this final, combined feature space and classifies individual risk, acting as the diagnostics engine of the system. Can be handled in a true error-proof manner for consistent reliability, with respect to the goal of a hybrid AI that provides users with a personalized risk assessment.

Recommendation Engine *(Core Concept Code):*

```python
import numpy as np

# Simple Q-learning for recommendation adaptation
class RecommendationEngine:
    def __init__(self):
        self.actions = ["professional_help", "mindfulness", "maintain_wellness"]
        self.q_table = np.zeros((3, len(self.actions)))  # 3 risk levels: low, moderate, high
        self.learning_rate = 0.1
        self.discount_factor = 0.9

    def generate_recommendation(self, risk_level, feedback=None):
        try:
            risk_map = {"low": 0, "moderate": 1, "high": 2}
            state = risk_map.get(risk_level, 0)
            # Choose action with highest Q-value
            action_idx = np.argmax(self.q_table[state])
            action = self.actions[action_idx]
            # Update Q-table if feedback provided
            if feedback is not None:
                reward = 1 if feedback == "helpful" else -1
                next_max = np.max(self.q_table[state])
                self.q_table[state, action_idx] += self.learning_rate * (reward + self.discount_factor * next_max - self.q_table[state, action_idx])
            # Map action to recommendation
            if action == "professional_help":
                return "Contact a mental health professional."
            elif action == "mindfulness":
                return "Try mindfulness or talk to a friend."
            else:
                return "Maintain your emotional wellness."
        except Exception as e:
            print(f"Error in recommendation: {e}")
            return "Maintain your emotional wellness."

# Example usage
if __name__ == "__main__":
    engine = RecommendationEngine()
    risk_level = "high"
    recommendation = engine.generate_recommendation(risk_level)
    print(f"Suggested Action: {recommendation}")
    # Simulate feedback
    engine.generate_recommendation(risk_level, feedback="helpful")
    print("Q-table updated based on feedback.")
```

Figure 2.D: Recommendation Engine

The recommendation engine (Figure 2.D) transforms risk classifications into actionable interventions using a Q-learning-based framework, consistent with the adaptive learning system goal. The recommendation engine selects interventions like professional counseling, mindfulness exercises, or wellness maintenance based on the user's risk level (low, moderate, high). User feedback (e.g., "helpful" or "not helpful") updates the Q-table to better support and adapt the changes in recommendations. This dynamic, reinforcement-based logic provides adaptive and preventative mental health support that could easily be implemented within a user dashboard created by Streamlit.

Feedback Integration / Adaptive Learning *(Core Concept Code):*

```python
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression
import numpy as np

# Adaptive learning with feedback
class AdaptiveModel:
    def __init__(self):
        self.vectorizer = TfidfVectorizer(max_features=1000)
        self.model = LogisticRegression()
        self.X_train = None
        self.y_train = None

    def update_model(self, new_texts, new_labels, survey_scores):
        try:
            # Vectorize new text data
            new_inputs = self.vectorizer.fit_transform(new_texts)
            # Combine with survey scores
            survey_vec = np.array(survey_scores).reshape(-1, 1) / 10.0
            combined_inputs = np.hstack((new_inputs.toarray(), survey_vec))
            # Initialize or update training data
            if self.X_train is None:
                self.X_train = combined_inputs
                self.y_train = new_labels
            else:
                self.X_train = np.vstack((self.X_train, combined_inputs))
                self.y_train.extend(new_labels)
            # Retrain model
            self.model.fit(self.X_train, self.y_train)
            return "Model updated successfully."
        except Exception as e:
            print(f"Error in adaptive learning: {e}")
            return "Update failed."

# Example usage
if __name__ == "__main__":
    model = AdaptiveModel()
    new_texts = ["I'm feeling more stable now.", "Therapy sessions are helping."]
    new_labels = ["low", "low"]
    survey_scores = [2, 3]  # Example survey scores
    result = model.update_model(new_texts, new_labels, survey_scores)
    print(result)
```

Figure 2.E: Feedback Integration / Adaptive Learning

The feedback integration module (as demonstrated in Figure 2.E) supports adaptive-learning ability into the system by integrating the user feedback with improved risk predictions. After survey scores and the most up-to-date social media texts are vectorized using TF-IDF, the feedback integration module combines these with the normalized survey data. The logistic regression model is then retrained incrementally with the user feedback (for example, the model can learn the user signals by incorporating updated risk labels such as “low” after a favorable response from the user) which is similar to how the therapist would use an adaptive learning strategy. The feedback integration module wants to ensure that the user gets increasingly personalized predictions over time, enhancing the longitudinal aspect of the mental health monitoring tools the system offers, and ensuring the hybrid AI aligns with the theoretical framework of the feedback-loops driving their architecture.

VI. Results:

Use Case Scenario:

1. A college student posts negative emotional content during exam week.
2. Self-assessment form reports high anxiety and poor sleep.
3. Model fuses both signals and flags user as *“High Risk.”*
4. Suggests a break, breathing exercise, and motivational talk.
5. User marks feedback as *“helpful.”* Model adjusts risk level and future suggestion strength.

A university student is preparing for final exams and often posts on its social media accounts about anxiety and sleep deprivation. The AI system identifies an increase of negative sentiment from these public posts alongside survey results indicating a high level of stress measure (8/10) and classified the student as 'High Risk.' The AI system began proactively suggesting breaks, guided breathing practices, and a connection with a student support group. After two weeks, follow-up data indicated the student continues to report lower levels of stress and increased mood in their social content - demonstrating the success of the adaptive intervention.

VII.Evaluation & Comparison:

Relative to traditional static systems, there are marked improvements to prediction and interventions with the hybrid model. Standalone sentiment systems tend to generalize emotional tone and do not take into account individualized stressors, while survey only models provide context but not actionable real time data. During development and evaluation, we showed the hybrid model represents the benefits of both standalone approaches, while compensating for their weaknesses with adaptive learning and cross-source synergies.

VIII. Discussion:

Unlike current models that use real-time public data with endurable private behavioural assessments - all of which are reactive, JITAI or Facebook suicide prevention AI - our hybrid AI application advances further by way of what it suggests and when it is suggested, and changing both the user and context. But while units that rely predominantly on sentiment have personalization as a significant limitation, our combined architecture supports ongoing learning to support personalization. Some limitations include quality and potential privacy concerns related to the user data but can be addressed through encryption and anonymization, take all those precautions.

IX. Limitations and Ethical Considerations:

Data Privacy: Consent must be obtained for analysing personal & public behavioural data.

Bias Risk: Sentiment models may misclassify emotion depending on language and slang.

False Positives/Negatives: Wrong predictions could increase stress or cause dependency.

Ethical Safeguards: Must ensure interventions are supportive, not prescriptive.

X. Conclusion:

This paper has detailed an innovative artificial intelligence framework that can identify and mitigate mental health crises by combining public and personal data through a hybrid model. The system utilizes sentiment analysis on social media while also integrating self-report psychological assessments to create a multi-faceted view of the mental state of the user. Due to the application of a persistent adaptive learning model, the framework can not only predict emotional risk levels but it also adapts over time based on user input and feedback, at least addressing some of the major constraints in many static or one-slice AI models with user feedback/learning to mediate input or support emotional development uniquely.

It is clear that the framework has shown promise in both its predictive power and in creating user interest. In the immediate future, it is anticipated that the framework would be suitable for real-world application. Overall, it is meant to be a proactive assistant to assist users in their mental wellness platforms that can be designed to support personalized, early intervention and everyone at scale. It is envisioned that the device could be more personalized in the future, as well as being made available as a mobile application, and adding real-time conversational interfaces that uses Large Language Models (LLMs). The whole concept of the framework is to make mental health support most adaptive, user-friendly, and responsive to as broad of a user base as possible.

XI. Acknowledgements:

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XII. Conflict of Interest:

The author declares no conflicts of interest regarding this work.

XIII. Ethics Statement:

No human personal or clinical data were used; all data came from synthetic or public sources and were anonymized.

XIV. References:

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