Bilkent University
Department of Computer Engineering

Senior Design Project

Team T2507

SCUBAMIND - MENTAL HEALTH

Project Specification Document

22103231 Merve Güleç merve.gulec@ug.bilkent.edu.tr

22103775 Metin Çalışkan metin.caliskan@ug.bilkent.edu.tr

22101998 Muhammed Fatih Başal fatih.basal@ug.bilkent.edu.tr

22103416 Murathan Işık murathan.isik@ug.bilkent.edu.tr

22103406 Yiğit Koşum yigit.kosum@ug.bilkent.edu.tr

Hamdi Dibeklioğlu

İlker Burak Kurt and Mert Bıçakçı

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1. Introduction

Depression has evolved into a pervasive global health crisis, significantly impacting the quality of life and productivity of millions of individuals. According to the World Health Organization (WHO), depression is a leading cause of disability worldwide, yet the diagnostic and therapeutic landscape remains fraught with challenges [1]. Traditional clinical psychiatry relies heavily on episodic consultations and self-reported questionnaires. While valuable, these methods suffer from inherent limitations: they depend on the patient's memory (recall bias), are subject to social desirability bias, and only capture a "snapshot" of the patient's mental state, failing to reflect the fluctuating nature of mood disorders in daily life [2].

ScubaMind is designed to bridge this gap by introducing a mobile-based, privacy-preserving, and continuous mental health monitoring system. Unlike traditional methods that require active user effort, ScubaMind leverages the concept of "Digital Phenotyping." By utilizing the sensors embedded in modern smartphones and wearable devices, the application collects behavioral and physiological data in the background without disrupting the user's routine.

By integrating advanced technologies, including Native Android Services for robust data collection, Speech Signal Processing for vocal biomarker analysis, and an Embedded AI Core for on-device inference, ScubaMind analyzes complex behavioral patterns to detect early signs of depression risks. Crucially, the system operates on a "Local-First" architecture, ensuring user privacy by processing sensitive data entirely on the device.

In this report, after a brief description of the project, its high-level architecture design diagram, constraints, requirements, and feasibility discussions will be thoroughly examined

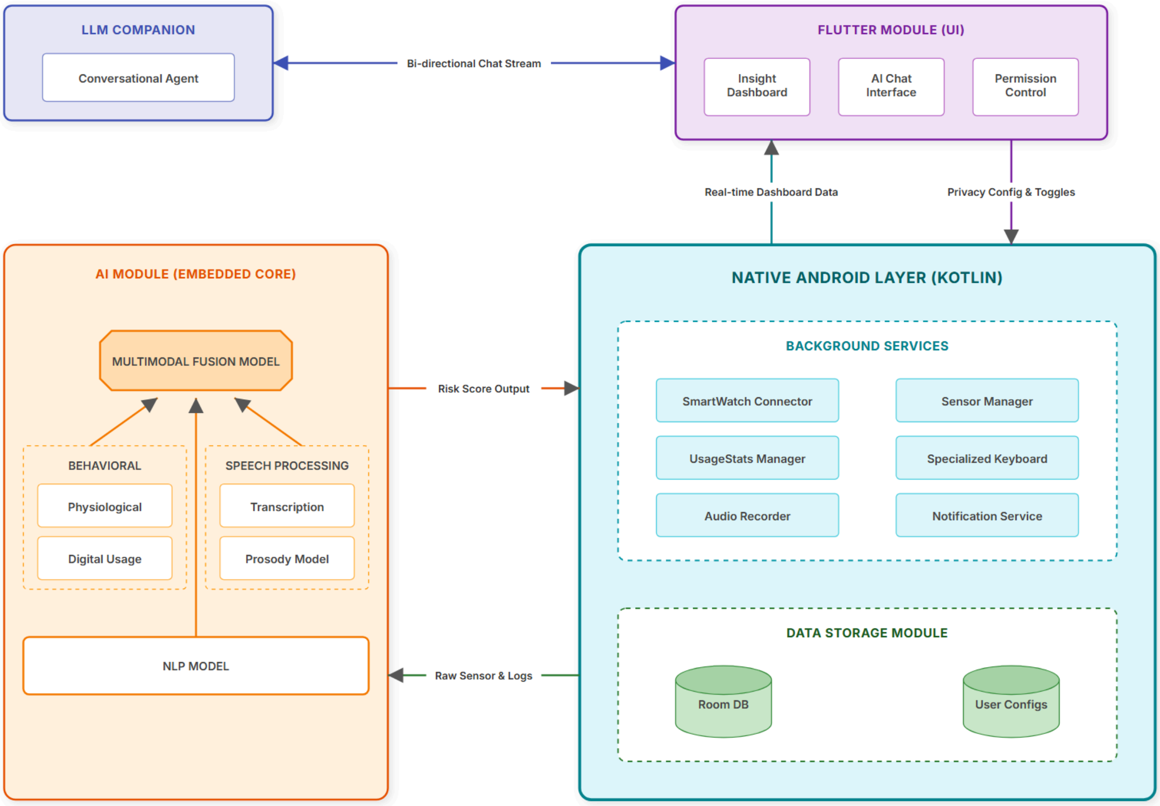
1.1 Description

This project aims to analyze behavioral data passively collected from users' smartphones and wearable devices through a mobile application called ScubaMind. To ensure high accuracy and context awareness, the system utilizes an embedded Multimodal Fusion Model. This model intelligently combines diverse data streams: physiological metrics (Heart Rate, HRV, etc.) from smartwatches, digital usage habits from the phone, and sentiment analysis derived from a privacy-preserving Custom Keyboard and Speech Processing module. These varied signals are fused locally to identify early depression risks effectively.

Beyond detection, ScubaMind functions as a personal support assistant. It features an LLM-powered Companion (Large Language Model) that provides users with empathetic conversation and personalized guidance, such as daily recommendations, mindfulness exercises, and mood monitoring via an interactive dashboard.

To protect the confidentiality of user data, the application performs all analysis processes, including the AI inference, on-device. This means data is processed locally without raw logs (like keystrokes or audio) ever being transferred to the cloud, ensuring strict user privacy. Additionally, users retain full control over their data and can share summary reports created by the application with their doctors if they wish.

1.2 High Level System Architecture & Components of Proposed Solution



ScubaMind is planned to have a layered architecture. The system consists of four main components:

1.2.1 Flutter Module

Purpose: Serves as the primary, cross-platform user interface designed for user interaction, data visualization, and system control. This layer acts as the secure bridge between the user and the complex on-device intelligence, transforming raw analytical outputs into actionable mental health insights while granting the user absolute authority over their data privacy.

Modules:

> **Insight Dashboard:** This module acts as the primary visualization tool, rendering complex mental health data into intuitive formats. It displays real-time PHQ-9 risk scores using gauge indicators and provides interactive charts for longitudinal trend analysis, allowing users to effortlessly track the correlation between their behavioral patterns and mood fluctuations. Also each individual feature is available for the user at feature specific pages providing the user with more detail on each feature.

AI Chat Interface (AI Companion): Designed as the central hub for active engagement if needed, this interface facilitates secure, bi-directional communication with the LLM Companion providing a user-friendly environment for self-expression while serving as an entry point for gathering semantic and acoustic data for analysis. Also the data from the depression indicators could be feeded into the prompt of the LLM to gather more focused data on user's needs.

Permission Control: This module empowers users with complete data sovereignty through a settings panel. It allows users to individually toggle specific sensor data streams (e.g., keyboard tracking, GPS variance) on or off and provides transparent options for managing data retention policies, including the immediate deletion of local storage.

Data Flow:

Flutter Module → LLM Companion: Establishes a real-time, bi-directional stream to transmit user chat inputs and journal entries. In return, it receives immediate, empathetic text responses and structured guidance from the conversational agent. If allowed, it also sends the user's current state for LLM to enhance the returns from the companion.

Flutter Module → Native Android Layer: Sends explicit user commands to the native backend to toggle specific background services (e.g., enabling/disabling the Custom Keyboard or Sensor Manager) and executes data sovereignty requests such as wiping local storage.

1.2.2 Native Android Layer (Data & Storage)

Purpose: Acts as the system's operational backbone, utilizing Kotlin-based background services to continuously retrieve, synchronize, and store data from hardware sensors, wearables, and system logs. It manages the entire data lifecycle by persisting raw logs in an encrypted local database and orchestrating essential background tasks, ensuring robust performance and data integrity without compromising user privacy.

Modules:

Background Services:

SmartWatch Connector: A specialized background service that interfaces with wearable devices via health APIs (e.g., Health Connect). It synchronizes physiological biomarkers such as Heart Rate and Heart Rate Variability (HRV) to monitor stress and sleep quality accurately.

Sensor Manager: This service continuously polls on-device hardware sensors, including the step counter location providers etc. It processes raw signals to extract mobility metrics like step count and movement variance, which are key indicators of psychomotor retardation.

UsageStats Manager: Leveraging Android's usage access permissions, this module logs digital interaction patterns such as screen time duration, app launch frequency, and unlock counts to identify behavioral anomalies associated with social withdrawal or sleep disruption.

Specialized Keyboard: Operating as a secure Input Method Service, this component extracts privacy-preserving text features in real-time. It ensures that raw keystrokes are processed in volatile memory without being persistently logged or transmitted.

Audio Recorder: Configured to capture high-quality audio samples during journaling sessions, this module manages microphone access and raw audio buffering. It prepares the audio data for subsequent on-device speech processing, ensuring optimal sample rates for feature extraction.

Notification Service: This local service manages the delivery of timely, context-aware alerts and daily reminders. It functions offline to encourage user engagement, prompting for mood check-ins or suggesting mindfulness exercises based on the latest AI inference results.

Data Storage Module:

Room Database: Serving as the central repository for the application, this encrypted SQLite abstraction layer securely persists all structured data, including sensor logs, inference history, and journal entries. It ensures data integrity and supports complex queries required for longitudinal analysis.

User Configs: Used to store sensitive cryptographic keys, user preferences, and privacy toggle states. This lightweight storage mechanism ensures that critical configuration data remains secure and instantly accessible to the application logic.

Data Flow:

Native Android Layer → AI Module: Pipes batched raw data (sensor logs, text embeddings, audio features) to the embedded AI core for inference. It also receives the calculated "Risk Score Output" back from the AI module to be stored in the database.

Native Android Layer → Flutter Module: Pushes real-time updates to the UI layer, including aggregated health metrics for the dashboard and status alerts (e.g., "Sensor Active") to keep the user informed.

Native Android Layer → Hardware/Sensors: Directly polls physical sensors and system APIs based on the configuration received from the Flutter module, strictly adhering to the user's privacy toggles.

1.2.3 AI Module

Purpose: Executes privacy-preserving, on-device multimodal inference. This core engine processes raw sensor, audio, and text logs locally to estimate depression severity, ensuring sensitive user data remains secure on the device.

Modules:

Speech Processing Module: Handles the raw audio input from the user session through two distinct pathways.

Transcription: Converts raw speech signals into textual data using an optimized on-device ASR model. This transcript captures the linguistic content of the interaction.

Prosody Model: Analyzes the acoustic properties of the voice. It extracts paralinguistic features such as tone, pitch variability, energy, and speech rate to quantify the emotional state independent of the spoken words.

NLP Module: A specialized Transformer-based engine that processes the textual data. It performs deep semantic evaluation to extract high-dimensional embedding vectors representing the user's sentiment, emotional context, and psychological patterns.

Behavioral: Aggregates and normalizes passive sensing data to provide contextual behavioral markers.

Physiological: Processes metrics retrieved from the phone and SmartWatch (Activity, Sleep, HR-HRV).

Digital Usage: Analyzes device interaction patterns to detect behavioral anomalies associated with depression.

Multimodal Fusion Model: The central decision-making unit of the architecture. It aggregates the disparate feature vectors from the Speech Proc., NLP Module, and Behavioral blocks. Using a fully connected neural network, it synthesizes these modalities to calculate and output a single, continuous Risk Score.

Data Flow:

Native Android Layer → AI Module: Transmits the raw sensor, audio, and phone usage data captured by the Data Retrieval services. This triggers the inference cycle by feeding the embedded core with the necessary multimodal inputs.

AI Module → Native Android Layer: Delivers the calculated Risk Score output and any relevant analysis metadata. This output is sent back to the Native Android Layer to be encrypted and stored in the Room DB, making it available to Flutter UI to display on the Insight Dashboard.

1.2.4 LLM Companion

Purpose: Acts as the empathetic interface of the system, providing real-time, interactive support. It leverages a Large Language Model to engage the user in natural, open-ended dialogue, simulating a supportive companion while facilitating the generation of verbal data for the analysis core.

Modules:

Conversational Agent: The core generative engine designed to manage user interactions. It utilizes prompt engineering and context management to generate responses that are psychologically safe. Also if permitted by user, processes the user state to produce more on point responses.

Data Flow:

Flutter Module → LLM Companion: Establishes a real-time, bi-directional stream to transmit user input. Additionally, if permitted by user, it forwards the current behavioral state to contextualize the interaction.

LLM Companion → Flutter Module: Streams the generated text responses back to the UI. This ensures the user receives an immediate response, fostering a continuous and engaging support loop.

1.3 Constraints

1.3.1 Implementation Constraints

Since the AI models run entirely on-device, the application is constrained by the CPU, RAM, and battery capacity of the user's smartphone. Hence, the models must have low energy consumption and not negatively impact battery performance. The Data Retrieval Module relies on Android's background service policies. Real-time components must process audio chunks with minimal latency to ensure a smooth user experience. This requires the use of highly optimized libraries.

1.3.2 Economic Constraints

The depression analysis runs free on the device; however, the LLM Companion relies on the external APIs. The project is constrained by the token costs of these APIs. In order to minimize the development cost, we will use free models and free libraries. Also, the AI models are heavy, hence they require smartphones with moderate to high processing power. This creates an economic barrier for the target audience.

1.3.3 Ethical Constraints

The application must adhere to a strict privacy-by-design framework where all raw data, including audio and keystrokes, is processed exclusively on-device and never transmitted to external servers. Users must retain absolute authority over their data, with mandatory features for informed consent, the ability to toggle individual sensors, and a "right to be forgotten" mechanism for immediate local deletion. As a non-diagnostic support tool, the system is prohibited from replacing professional medical judgment and must implement crisis management protocols to direct users to professional resources upon detecting critical risks. Furthermore, algorithmic integrity is required to be maintained through regular audits to ensure the AI models remain free from bias against specific demographics or behaviors.

1.4 Professional and Ethical Issues

Issue: Users may fear that the continuous collection of highly sensitive data, particularly via the custom keyboard and microphone, constitutes surveillance or risks exposing private content like passwords or conversations.

> **Mitigation:** The system employs a strict **Local-First** architecture where raw data (keystrokes, audio streams) is processed in short time in volatile memory to extract feature vectors and is never persistently stored or transmitted to the cloud. Additionally, users are provided with granular control to toggle specific sensors off at any time via the Permission Control without losing full application functionality.

Issue: There is a significant risk that users may misinterpret the AI-generated "Depression Risk Score" as a definitive medical diagnosis, potentially leading to unnecessary anxiety (nocebo effect) or self-medication.

> **Mitigation:** The application explicitly frames all outputs as "behavioral insights" and "estimations" rather than clinical diagnoses. All scores and charts are accompanied by prominent disclaimers emphasizing that ScubaMind is a decision-support tool, and users are strongly encouraged to consult healthcare professionals for medical validation.

Issue: The LLM-powered conversational agent might inadvertently provide inappropriate advice during critical mental health episodes or fail to recognize immediate risks of self-harm.

> **Mitigation:** The conversational agent is designed with strict safety guardrails and keyword detection algorithms. Upon detecting crisis indicators or suicidal ideation, the system suspends the standard chat flow and immediately redirects the user to emergency resources and professional helplines, acting solely as a bridge to help rather than a therapist.

Issue: The AI models (Speech Processing and NLP) could exhibit bias against specific dialects, speech patterns, or cultural writing styles, potentially yielding inaccurate risk assessments for certain demographics.

> **Mitigation:** The **Multimodal Fusion** approach mitigates single-source bias by cross-referencing physiological data (HRV, Sleep) with behavioral logs; for instance, a naturally slow speaker won't be flagged solely on prosody if their physical activity is normal. Furthermore, models are selected and tuned to ensure fair performance across diverse user groups.

1.5 Standards

The following standards and guidelines were used as a basis in the project development process:

HL7 FHIR (Fast Healthcare Interoperability Resources): HL7 FHIR is the industry standard for the secure, reliable and standardized sharing of the electronic health data. We adopt the FHIR data structure for storing the calculated Risk Score and analysis logs within the local database [3].

ISO/IEC 27001: Due to the processing of sensitive mental health data, ScubaMind strictly adheres the Privacy by Design principles, which aligns with ISO/IEC 27001 controls. This standard dictates that data protection is not an afterthought but an architectural requirement [4].

GDPR & KVKK: The application processes sensitive data, so strict adherence to GDPR (General Data Protection Regulation) and KVKK (Personal Data Protection Law) is mandatory. These regulations dictate the project's data governance strategy, ensuring confidentiality and security [5].

IEEE 11073: This standard defines the protocols for data exchange between personal health devices and external computer systems. In our project, IEEE 11073 guidelines are utilized within the Data Retrieval Module to standardize the collection of physiological metrics (e.g., heart rate variability, sleep patterns) from various wearable health devices [6].

UML 2.5.1 (Unified Modeling Language): UML 2.5.1 is utilized as the standardized visual modeling language to architect the system's complex components [7].

2. Design Requirements

2.1. Functional Requirements

This section covers the basic functionality that the ScubaMind application will provide to the user and the behaviors the system must implement. The requirements are defined to be user-focused, clear, and applicable.

2.1.1. User Management

- A user-specific profile screen should be available, and users should be able to edit their personal information.
- After downloading the app, users should go through a brief onboarding process and be able to select their personal preferences (notification preferences, data sharing permission, wearable device connection, etc.).

2.1.2. Passive Behavioral & Sensor Data Collection

- The app should support the collection of daily user behavior without active participation, only with the necessary permissions.
- The system should automatically collect phone behavior data (screen on/off, screen time, app usage frequency).
- Keyboard usage characteristics (typing speed, interaction intensity, etc.) should only be analyzed in an anonymized form.
- Phone sensor data (accelerometer, gyroscope, step count, movement intensity) should be recorded regularly.
- The app should be able to integrate heart rate, sleep patterns, and activity data from wearable devices.
- All data collection processes should be conducted on-device and encrypted, in accordance with Privacy by Design principles.
- Users should be able to manage their data collection permissions.

2.1.3. On-Device Data Analysis & Mood Prediction

- The system should analyze passive data collected using machine learning models running on the device to provide meaningful feedback to the user.
- On-device ML models should analyze the user's daily behavioral patterns at regular intervals.
- The user should be presented with a mood prediction (categories such as "Energetic," "Low," "Stressed," and "Balanced").
- The system should be able to assess depression risk and inform the user of low, medium, or high risk levels.
- All analyses should be performed solely on the device.
- Analyses should be optimized to maintain energy efficiency.

2.1.4. Personalized Recommendations and Support System

- The app should provide personalized support and behavioral recommendations to the user based on analysis results.
- Daily recommendations (such as reminders for short walks, breathing exercises, suggestions for taking breaks, etc.) should be created specifically for the user.
- Recommendations should be dynamically updated based on the user's behavior and mood changes throughout the day.
- In certain situations, and with user permission, the system can send the user "supportive notifications" (e.g., "You haven't been very active today. A 30-minute walk would be beneficial").
- All recommendations should be based on scientific sources and verified content.
- The LLM agent integrated should guide the user correctly in order to not cause any discomfort or incompatibility with app’s aims.

2.1.5. Reporting and Visualization

- The app should present its data with clear and effective graphs to help the user better understand themselves.
- The user's daily, weekly, and monthly behavioral and mood trends should be displayed graphically.
- User activities, sleep patterns, and mood changes should be displayed in a timeline format.
- The app should generate a summary PDF report that the user can share with their doctor upon request.
- Reports should only be stored on the user's device or shared with the user's express consent.

2.1.6. Notification Management

- The system should send supportive notifications to the user at the right time.
- The system should send intelligent notifications based on recommendations, activity goals, and user behavior.
- Notifications should be optimized to avoid unnecessary alerts (not create stress).

2.1.7. Security and Privacy Requirements

- The app must protect users' personal and behavioral data in accordance with the highest security standards.
- All data must be stored on the device.
- User data must never be shared with third parties.

2.2. Non-Functional Requirements

Non-functional requirements define the overall metrics for the ScubaMind app, related to user experience, performance, reliability, and maintainability. These requirements determine whether the app will not only function, but also be efficient, secure, accessible, and supportable over the long term.

2.2.1 Usability

- The application should have a simple, calming, and user-friendly interface.
- The user onboarding process should be intuitive and guide the user step-by-step.
- All user interactions should be achievable with no more than 4-5 taps.
- Graphs, reports, and mood displays should be easy to understand and have a clear visualization language.
- The application color palette should conform to the "soft-tone" themes recommended for mental health applications.

2.2.2 Reliability

- The system must process collected data accurately and ensure high accuracy in analysis.
- Data loss must be prevented even when the application is running in the background.
- The application must allow its core features to function even without a network connection.

2.2.3 Performance

- Machine learning models should operate with low power consumption and minimally impact battery usage.
- The application interface should respond with a maximum latency of 300 ms (the user experience limit).
- Graphics rendering should be smooth, even on low-end devices.
- Data processing tasks should not strain the device; analyses should be performed using optimized batch processes.
- The application should be able to run without requiring an internet connection.

2.2.4 Supportability

- The system should be designed to work seamlessly across different Android versions.
- The application's code structure should follow a modular architecture suitable for growth.
- Third-party dependencies (SDKs, sensor APIs) should be regularly monitored.

2.2.5 Scalability

- The application must operate without experiencing performance degradation as the number of users increases.
- Analytics modules must be extensible to support new data types that may be added in the future.
- Application performance should not degrade as user reports and behavioral history increase; data processing structures should be optimized accordingly.

3. Feasibility Discussions

3.1. Market & Competitive Analysis

The following analysis aims to define ScubaMind's place in the digital mental health ecosystem, reveal the current dynamics of the market, and compare it with competing applications.

3.1.1. Market Outlook

Digital mental health apps have gained momentum over the last five years, driven by both user demand and technological advancements. Grand View Research's 2024 report predicts that the global mental health apps market will be valued at $7.48 billion in 2024 and reach $17.5 billion by 2030 [8]. This growth represents a compound annual growth rate of approximately 14–15%. Similarly, Mordor Intelligence's 2025 analysis projects the market to be worth $8.5 billion in 2025 and reach $18.5 billion by 2030 [9]. This data demonstrates that interest in digital mental health solutions is not fleeting; rather, it is a rising, consistent, and strong trend worldwide.

The primary drivers for this market growth are:

- The prevalence of conditions such as depression and anxiety (especially among young adults).
- Smartphones and wearable devices have become an integral part of daily life.
- Increasing reliance on digital health solutions in the post-COVID-19 era.
- Users are turning to low-effort, smart, and personalized solutions.

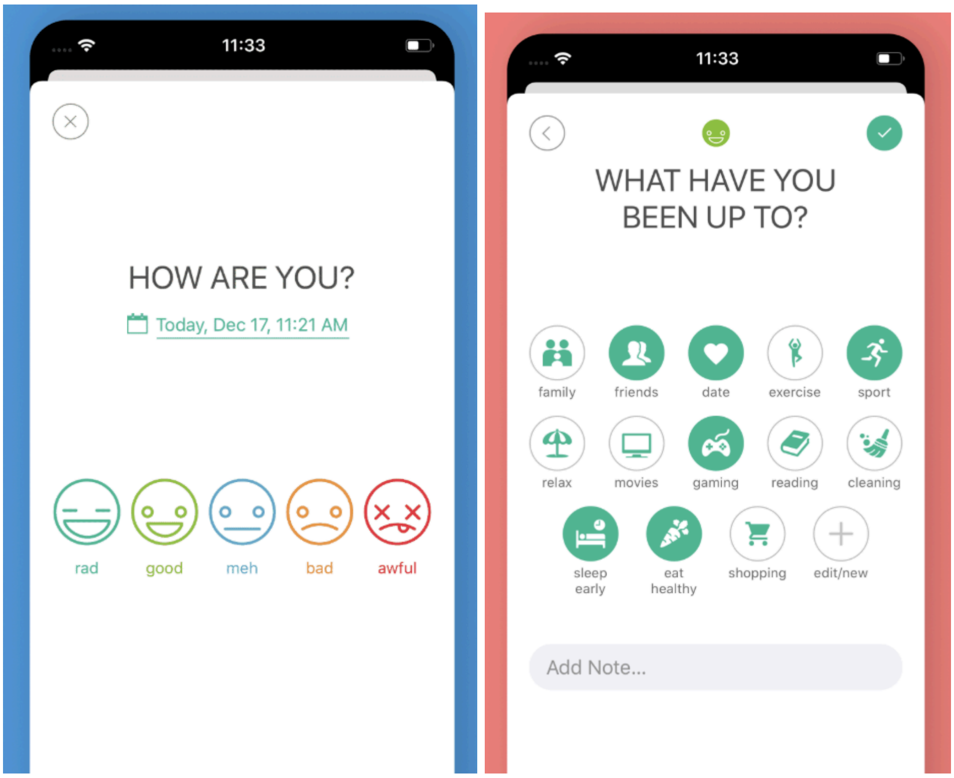
This overall picture demonstrates that ScubaMind's market segment is both open to growth and in need of innovative approaches.

3.1.2. Competitive Landscape Analysis

While there are many well-known applications in the digital mental health space, the majority of these are content-driven or one-dimensional tracking systems that require manual user input. ScubaMind distinguishes itself with its passive behavioral data collection and wearable integration. Five applications that serve similar purposes to ScubaMind are analyzed below.

Daylio – Self-Care Bullet Journal with Goals Mood Diary & Happiness Tracker

Daylio is a simple, habit-building mood journaling app that has reached many users worldwide [10]. Users manually mark their daily moods with emojis and hashtags, and the app graphs this data over time to visualize trends.



Pros: User-friendly, minimal design suitable for people of all ages; supports manual mood journaling, making it easier for users to express themselves; includes trend graphs that clearly display mood changes over time; and has verified ease of use thanks to a global user community.

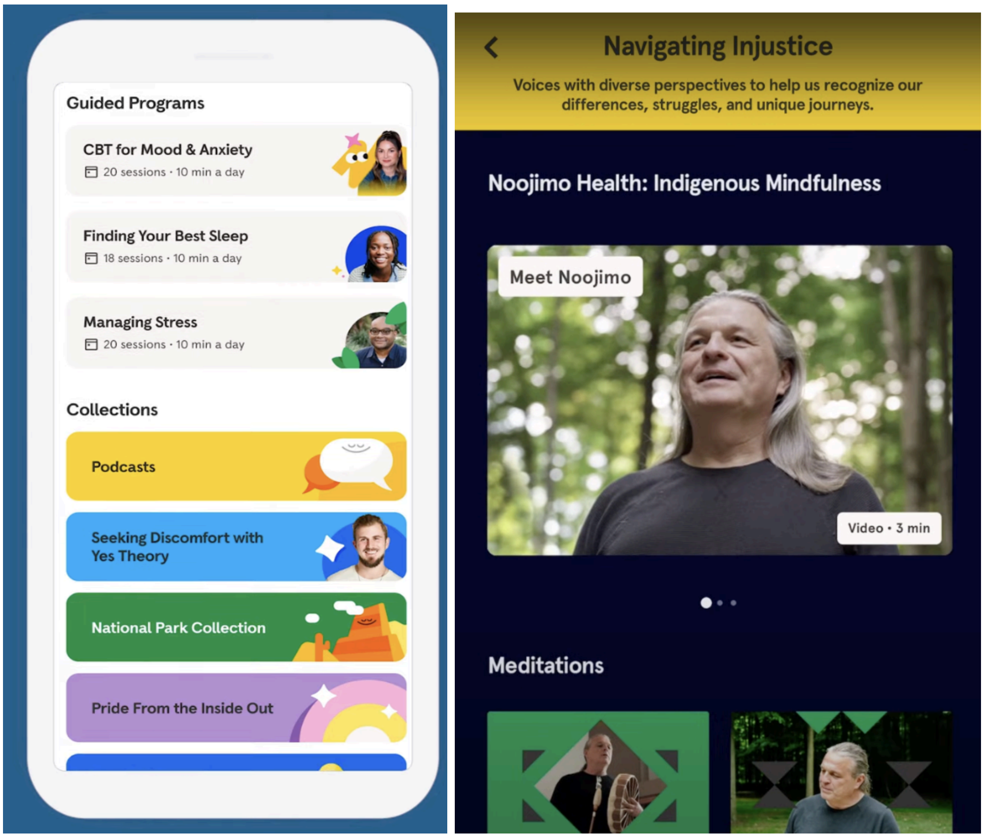
Cons: Relies entirely on manual input, meaning no data is generated unless the user marks their mood; offers no passive data collection; and does not provide clinical-level analysis, functioning more as a journaling app.

Comparison with ScubaMind: Unlike Daylio, ScubaMind automatically infers mood from user behavior, sensor data, and wearable data rather than relying on manual input. ScubaMind continues its analysis even if the user doesn't log in regularly, and in addition, it offers more advanced functions such as depression risk detection, personal recommendations, and report generation.

The application usage can be viewed [here](#).

Headspace – Mindfulness & Meditation Platform

Headspace is a wellness app known for its content such as meditation, breathing exercises, stress reduction techniques, and sleep support [11]. The goal is to provide users with a content ecosystem that provides mental relaxation.



Pros: Rich content library including meditation, sleep stories, and breathing routines; scientifically-based mindfulness programs with psychologist-verified content; high brand credibility and a strong community; and guided meditations that are ideal for beginners.

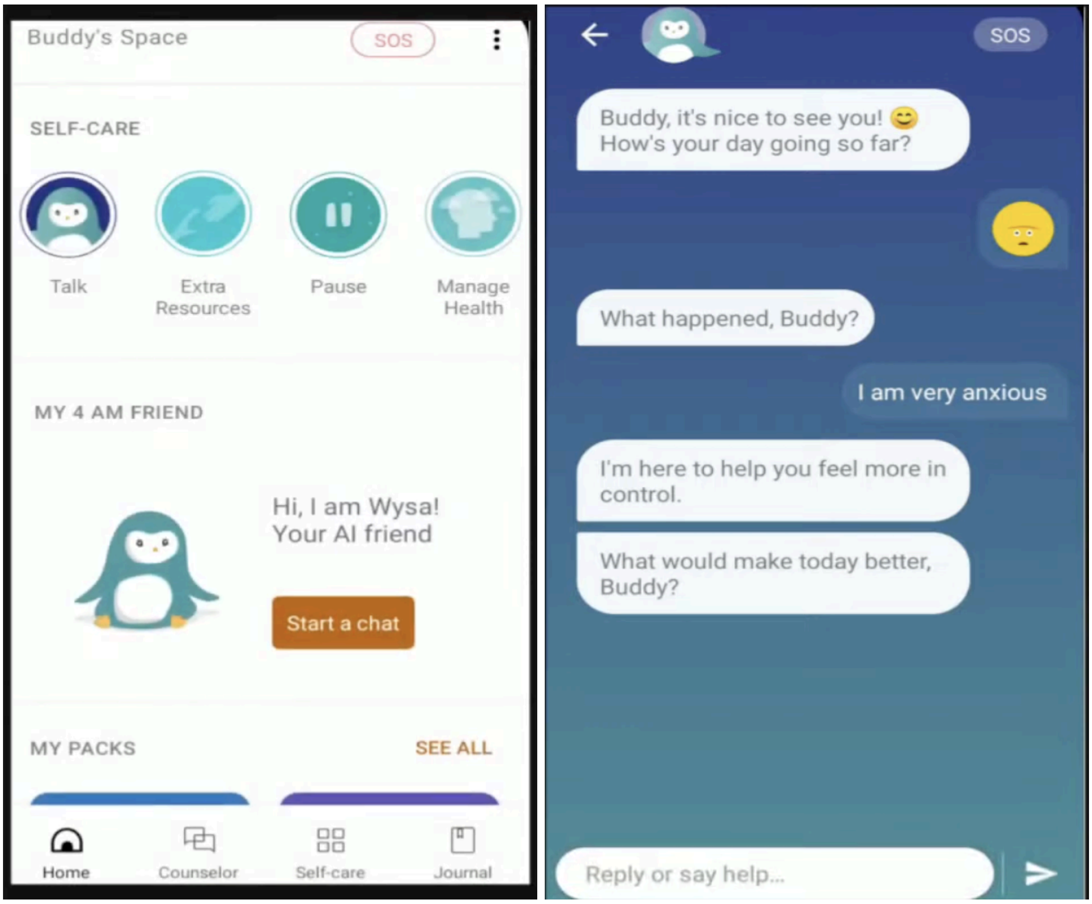
Cons: No mood tracking; no behavioral data collection; and the app focuses on content consumption, not personal analysis.

Comparison with ScubaMind: While Headspace offers content, ScubaMind analyzes user behavior and provides personalized guidance rather than content creation. Because ScubaMind's focus is on guidance and early risk detection, it is a much more proactive system than Headspace.

The application usage can be viewed [here].

Wysa – AI Chatbot for Mental Health

Wysa is an AI-powered mental health app that provides users with supportive, psychological first aid-style conversations. It uses guided guidance, cognitive behavioral therapy (CBT)-based exercises, and empathetic dialogue coto help users deal with stress, anxiety, and emotional challenges. The app focuses primarily on chat-based support rather than data-driven behavioral analysis [12].



Pros: AI-powered therapeutic chat that allows the user to express themselves; interactive exercises incorporating CBT and DBT techniques; and provides a smoother, more "human-like" user experience.

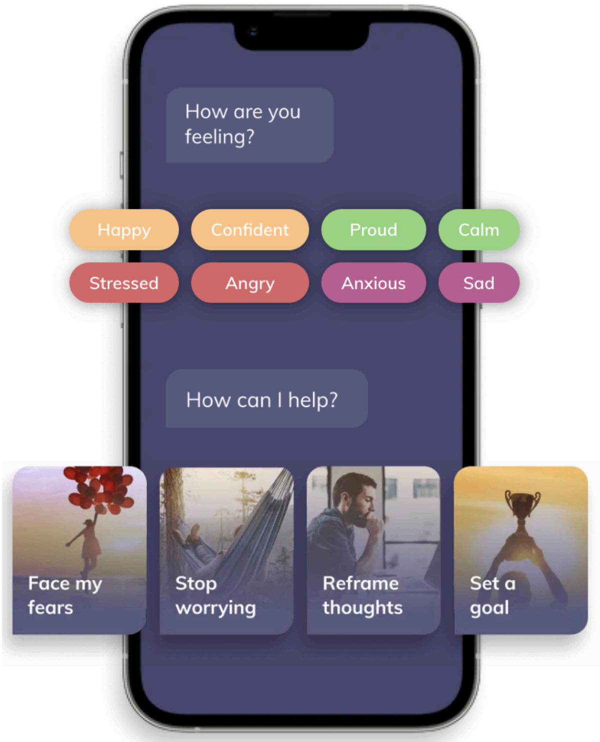
Cons: Does not support passive data collection; has no wearable and sensor integration; offers limited clinical assessment power; chat accuracy depends on the quality of the AI model; and depression risk analysis is not performed using a scientific model.

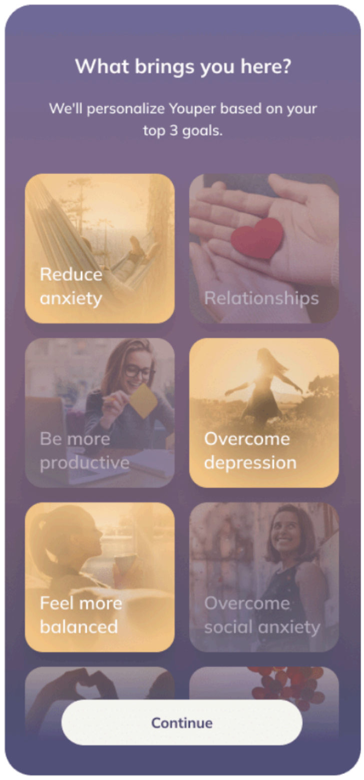
Comparison with ScubaMind: ScubaMind is not a chat app; instead, it relies on data-driven analysis, automated assessment, and personalized behavioral recommendations. However, it also has a chatbot that offers supportive conversations. ScubaMind's analysis is multidimensional, incorporating behavior, physical activity, sleep, and device usage.

The application usage can be viewed here.

Youper – Emotional Health Assistant

Youper provides users with essential digital support by offering AI-based emotional conversations, short meditations, and mood journaling. The app facilitates users' expressing their immediate emotions and aims to foster emotional awareness through guided short conversations. It also aims to promote mental well-being through short meditation exercises and daily assessments [13].





Pros: AI-powered chat and sentiment analysis allow users to express their feelings more easily and increase emotional awareness. Short daily assessments make it easier to track mood swings throughout the day. Simple reporting features also allow users to see their own mood trends.

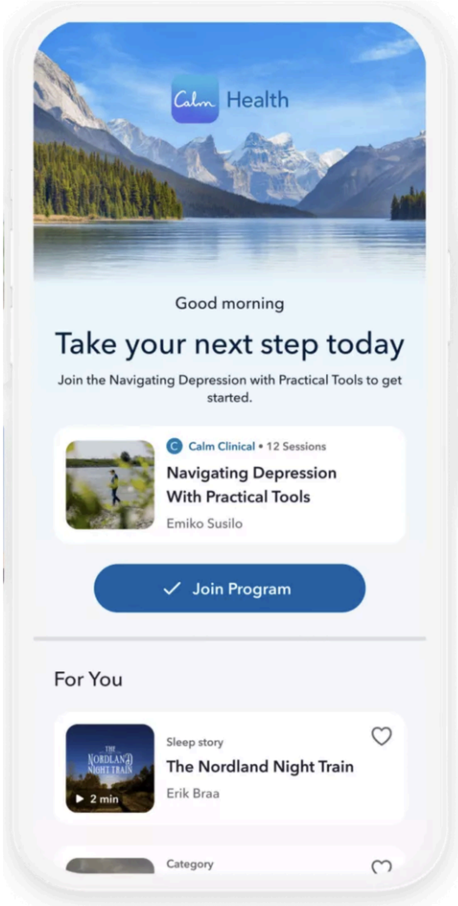
Cons: Because it doesn't collect passive data, the app relies entirely on active user use, and analysis is interrupted by inconsistent use. The lack of Wearable integration prevents the analysis of important life rhythm data such as sleep, activity, or heart rate. Therefore, the app is limited in providing a comprehensive mental health assessment.

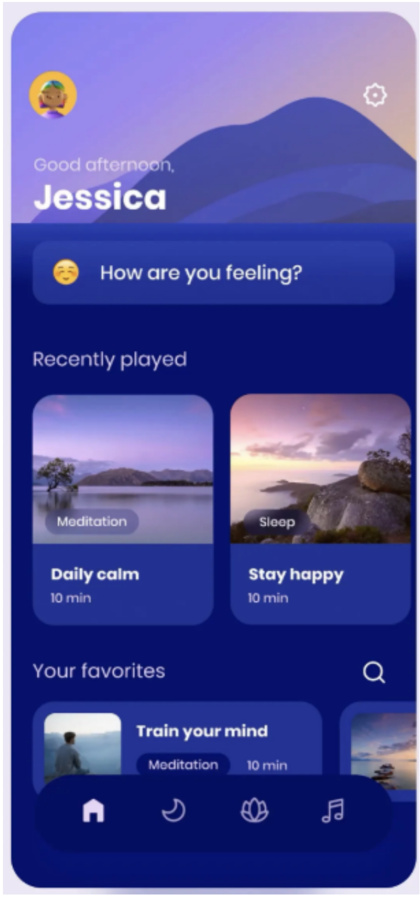
Comparison with ScubaMind: ScubaMind's data source isn't limited to conversations alone. By combining daily life patterns, device usage, and sensor data, it can use scientific models to predict depression risk. This allows it to detect changes in user behavior earlier and offer more personalized, proactive recommendations. In this respect, ScubaMind offers a much more comprehensive and data-driven assessment than chat-focused apps.

The application usage can be viewed [here](#).

Calm – Meditation and Sleep Management

Calm is a relaxation platform offering meditation, breathing techniques, sleep music, and mindfulness content. It boasts a broad content ecosystem aimed at reducing users' stress, improving sleep quality, and promoting mental balance [14].





Pros: Calm boasts one of the largest collections of meditation and sleep content. Its relaxing interface and professional voice-overs make using the app a truly enjoyable experience. Content on various themes, such as sleep, stress management, and breathing exercises, also helps users achieve relaxation in their daily lives.

Cons: As it does not collect passive data, it analyzes whatever data the user enters, which can lead to bias. It leaves usage largely up to the user, requiring them to explore their own shortcomings, which can lead to inaccurate self-assessments.

Comparison with ScubaMind: While Calm is a more content-focused relaxation app, ScubaMind is an early warning system that analyzes behavior and sensor data. While Calm aims to reduce the user's immediate stress, ScubaMind monitors long-term behavioral changes and can identify potential risks. Therefore, Calm stands out as a tool for mental relaxation, while ScubaMind processes the user's real-life data to provide a more personalized and proactive assessment.

The application usage can be viewed [here](#).

3.1.3. ScubaMind's Market Position

A review of the applications above reveals three main categories in the market:
- Manual mood-tracking applications (Daylio)
- Mindfulness & meditation applications (Headspace, Calm)
- Chatbot-based emotional support applications (Wysa, Youper)

However, no application combines the following components that ScubaMind offers on a single platform:

- Passive behavioral data collection (screen time, activity, typing rhythm)
- Wearable integration (heart rate, sleep cycle)
- Mood prediction and depression risk analysis with on-device ML
- User-specific behavioral recommendations (breathing, walking, routine recommendations)
- Doctor-sharable reports

With these aspects, ScubaMind is both technically innovative and sustainable in terms of user experience.

3.1.4. General Evaluation

When examining the digital mental health market, it becomes clear that most existing apps serve a single purpose: some offer only manual emotion tracking, others focus on meditation content, and still others offer only chat-based support. While these apps address specific needs, they are limited in capturing real-world changes in users' daily behaviors and assessing their risk of early-stage depression.

This is where ScubaMind's advantage becomes evident. By combining passive behavioral data, wearable device measurements, and daily usage habits, the app interprets the user's mood in a much more holistic way. This allows the system to continue running in the background, even if the user isn't actively opening the app, generating insights into long-term behavioral changes. The on-device analysis approach is important for privacy and enhances user trust.

In these respects, ScubaMind offers a modern mental health support system that integrates personalized recommendations, behavioral awareness, and early warning mechanisms into a single platform, unlike the fragmented experience offered by existing apps on the market. Therefore, ScubaMind is both aligned with today's digital health trends, where user needs are evolving, and represents a data-driven approach that is still largely lacking in the market.

3.2 Academic Analysis

The design of ScubaMind is rigorously grounded in the convergence NLP for Mental Health, Mobile Sensing, and Digital Phenotyping. By synthesizing methodologies from recent academic literature, the platform ensures that its depression risk assessment is not merely correlational but rooted in validated behavioral and cognitive biomarkers.

A primary pillar of the system is the inference of user personality and cognitive state through passive interaction data. Research by Gönç and Dibeklioğlu demonstrates that accurate depression severity estimation requires more than simple sentiment analysis; it necessitates a unified architecture that integrates emotion, sentiment, and personality features[15]. ScubaMind adopts this holistic view but extends the source of personality inference beyond text. Drawing on the findings of Peltonen et al., the system utilizes aggregated application usage patterns as a proxy for personality traits[16]. Peltonen's study confirms that analyzing app usage at the category level (e.g., frequency of "Communication" vs. "Game" apps) yields prediction fits of up to 96% for Big Five traits. ScubaMind leverages this insight in its UsageStats Manager, processing privacy-preserving category data to construct a stable personality baseline, which allows the AI core to distinguish between a user's habitual introversion and acute depressive withdrawal.

In parallel to digital usage, the system employs advanced mobility analysis to detect physiological symptom of depression. The foundational work "Trajectories of Depression" by Canzian and Musolesi establishes that mobility metrics derived from GPS traces specifically Radius of Gyration and Routine Index exhibit significant correlation with PHQ-8 scores[17]. ScubaMind incorporates these specific metrics into its Sensor Manager. By calculating the Routine Index to quantify deviations in a user's daily spatiotemporal structure, the system can identifying "reduced mobility" and "limited willingness to perform activities," which Canzian and Musolesi identify as strong indicators of depressive state changes, often before subjective symptoms are self-reported.

Furthermore, the system addresses the challenge of generalization across diverse user behaviors. The GLOBEM study by Xu et al. highlights that individual differences pose the greatest barrier to robust mental health modeling[18]. To mitigate this, ScubaMind adopts a "behavior continuity" approach inspired by Xu et al.'s findings. Rather than relying on static, population-wide thresholds, the Multimodal Fusion Model focuses on analyzing the continuity and disruption of the user's own historical data. This aligns with the personalized modeling approach advocated by Canzian, ensuring that the system is sensitive to the user's unique baseline rather than a generic average[17].

In conclusion, ScubaMind integrates the text-driven cognitive analysis proposed by Gönç and Dibeklioğlu , the app-usage-based personality profiling validated by Peltonen et al., and the mobility-based depression markers defined by Canzian and Musolesi [15][16][17]. This multi-dimensional academic foundation ensures a system that is scientifically valid, technically robust, and strictly privacy-preserving.

4. Glossary

Affective Computing: Computing techniques designed to recognize and interpret human emotions for analysis or interaction.

Background Service: An Android system component that runs tasks or collects data continuously in the background.

Behavioral Markers: Measurable signs reflecting changes in a user's mood or behavior. For example, disruptions in sleep patterns, a decrease in step count, an increase in screen time, or a decrease in social interactions.

Circadian Rhythm: The biological cycle regulating sleep, activity, and alertness patterns throughout the day.

Context Window: The portion of past conversation or data that a language model can consider when generating responses.

Data Minimization: A privacy principle that requires collecting only the amount of data necessary for the system to function.

Depression Risk Assessment (DRA): An algorithmic analysis process that predicts a user's tendency toward depression based on their behavioral and biometric data.

Depression Screening: The initial assessment phase to identify early signs of depression; it is not a clinical diagnosis but provides preliminary information about risk.

Differential Privacy (DP): A privacy method that introduces statistical noise to prevent identification of individual users during analysis.

Digital Behavior Indicators: Metrics representing how users interact with their devices, such as screen time, app usage, or unlock frequency.

Digital Mental Health Application: Software systems that use digital technologies (mobile applications, web platforms, wearable devices) to support, assess, or monitor users' mental health.

Digital Phenotyping: Digital characterization of an individual's behavior, routines, and mood using data from smartphones and wearable devices.

Early Warning Signals (EWS): Behavioral or physiological changes that may indicate emerging mental health risks.

Embedding: A numerical vector representation that captures the semantic or acoustic meaning of input data.

Encrypted Storage: A secure data storage mechanism in which information is encrypted to ensure confidentiality.

Feature Extraction: The process of transforming raw data into structured features that can be analyzed by machine learning models.

Health Connect API: An Android health data interface that synchronizes wearable metrics such as heart rate, sleep, and activity levels.

HL7 FHIR (Fast Healthcare Interoperability Resources): An international health data standard used for the secure and standardized sharing of electronic health data.

HRV (Heart Rate Variability): A physiological measure representing the variation between consecutive heartbeats, often used to assess stress or recovery.

Input Method Service (IMS): The Android framework that enables creating and managing custom keyboards.

ISO/IEC 27001: An international standard for information security management systems; it defines data privacy, integrity, and availability requirements.

LLM (Large Language Model): A generative language model used to provide conversational support and process user inputs.

Local-First Architecture (LFA): A design principle in which sensitive data is processed on-device first, avoiding unnecessary cloud transmission.

Longitudinal Analysis: The study of behavioral or biometric data collected across extended time periods to observe trends.

Mood Tracking: Monitoring the user's mood over time; can be done through manual input or automated analysis.

Multimodal Fusion (MMF): The combination of multiple data types, such as audio, text, movement, and biometric signals, into a unified predictive model.

On-Device Inference: The execution of machine learning models directly on the user's device rather than in the cloud.

On-Device Machine Learning (ODML): Machine learning models are not trained, but rather run on the device. Mood prediction or risk analyses are completed without sending data outside the device.

On-Device Processing (ODP): Collecting data is processed directly on the user's device, without being sent to the cloud. This method increases privacy and reduces the risk of data leakage.

Passive Behavioral Data: Daily behavioral data (e.g., screen time, step count, sleep duration, sensor data) automatically collected from devices without requiring the user to do anything.

Personalized Recommendations: Automatically generated personalized recommendations based on the user's behavior and analysis results (e.g., walk reminder, breathing exercise, break recommendation).

PHQ-9 (Patient Health Questionnaire-9): A standardized nine-item questionnaire used to measure depressive symptoms.

Privacy by Design: The principle of designing a system with user privacy at the forefront from the outset.

Prosodic Features: Acoustic elements such as pitch, tone, and speech rate used to evaluate emotional content in voice.

Prompt Engineering: Techniques used to design and adjust prompts in order to optimize outputs generated by language models.

Psychomotor Activity: Physical movement levels that reflect mental and behavioral states, often measured through sensors.

Room Database: An encrypted and structured local database solution used within Android applications for persistent storage.

ScubaMind: A mobile application project that analyzes behavioral data passively collected from smartphones and wearable devices to provide mood prediction, depression risk assessment, and personalized recommendations.

Sensor Data: Raw data from sensors on phones or wearable devices (accelerometer, gyroscope, pedometer, heart rate, ambient light, etc.).

Sentiment Analysis: The computational process of identifying the emotional tone or attitude within spoken or written user input.

State Management: A method in Flutter that organizes and controls how data changes are reflected on the interface.

Summary Report: A generated document containing the user's behavioral and mood-related information, typically formatted for optional sharing with professionals.

Trend Visualization: The graphical representation of behavioral or emotional trends across days, weeks, or months.

UML 2.5.1 (Unified Modeling Language): Standardized modeling language used to visually model system architecture, components, and user interactions; includes use case, class, and activity diagrams.

User Consent: The user's explicit and informed consent for the collection and processing of their personal and behavioral data.

User Data Sovereignty: The principle that users fully control their personal data, including access, permissions, and deletion rights.

Wearable Devices: Portable electronic devices such as smartwatches and wristbands that can collect physical and biometric data such as heart rate, step count, and sleep cycles.

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