**Project Work Submission Report**

**Personalized AI-Powered Mental Health Companion (PAI-MHC)**
**Submission Date:** September 27, 2025
**Project Deadline (PoC):** November 20, 2025

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**1. Group Details and Role Allocation**

**Group Members:**

- Sourav Bera
- Edwin Eldhose
- Suragani Yaswanth Sai
- Bindu Vamsi Guntupalli
- Avuthu Meenu Sree *(placed – not active)*

**Note on Role Allocation:**
At this stage of the project, no fixed individual roles have been assigned. All members will work collaboratively across all technical and non-technical aspects, with responsibilities distributed dynamically according to project requirements, expertise, and availability. This ensures flexibility, collective ownership, and balanced workload management during the Proof-of-Concept (PoC) phase.

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**2. Project Objectives**

The primary aim of the PAI-MHC project is to create an accessible, personalized, and data-driven platform that bridges the gap in timely mental health support.

- **Real-Time Empathetic Support:** Develop an AI conversational agent capable of delivering real-time, empathetic, and context-aware emotional support.
- **Multimodal Emotional Analysis:** Utilize advanced NLP models to accurately detect user sentiment, tone, and emotional states from conversational data.
- **Holistic Wellness Monitoring:** Integrate physiological data (heart rate, sleep quality, activity) from third-party wearable devices to create a comprehensive view of user well-being.
- **Personalized Intervention Recommendation:** Implement a recommendation engine that suggests tailored, evidence-based therapy and wellness activities (e.g., CBT modules, guided meditation) based on combined emotional and physiological data.

- **Scalable and Secure MLOps:** Establish a production-ready MLOps framework for continuous integration, deployment, monitoring, and automated retraining of all AI/ML models.
- **Actionable Insight Visualization:** Deliver intuitive dashboards for users and professionals to track mood trends, stress indicators, and intervention effectiveness over time.

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### 3. Real-life Problem Reference

**Problem:** The Global Mental Health Access and Personalization Gap

- **Access and Affordability:** Wait times for qualified human therapists are often months long, and private therapy is cost-prohibitive for the general population.
- **Inconsistent Monitoring:** Current support relies heavily on patient self-reporting during infrequent sessions, leading to recall bias and missed identification of real-time stress triggers or physiological decline (e.g., sleep loss, elevated resting heart rate).

**Solution Reference:** PAI-MHC directly addresses this by providing 24/7, stigma-free, on-demand support via an AI companion, complemented by objective physiological data from wearables. This creates a proactive, data-driven system for early intervention and personalized care that scales globally at a fraction of the traditional cost.

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### 4. Literature Review (Selected References)

| Reference | Core Topic | Quality Score (1-5, 5 being highest) | Contribution to PAI-MHC |
|---|---|---|---|
| "Multimodal Machine Learning in Mental Health: A Survey of Data, Algorithms, and Challenges" | Multimodal Fusion & Predictive Analytics | 5/5 | Confirms the superior diagnostic and prognostic accuracy achieved by fusing text, speech, and physiological signals over single-modality approaches. |
| "Can I Trust This Chatbot? Assessing User Privacy in AI- | GDPR/HIPAA & Trustworthiness | 5/5 | Highlights the critical gaps in user data protection and compliance for AI chatbots, |

| Reference | Core Topic | Quality Score (1-5, 5 being highest) | Contribution to PAI-MHC |
|---|---|---|---|
| Healthcare Chatbot Applications" | | | mandating a rigorous, security-first architecture. |
| "Randomized Trial of a Generative AI Chatbot for Mental Health Treatment (Therabot Trial)" | LLM Efficacy & Empathy | 5/5 | Provides clinical validation that fine-tuned Generative AI chatbots yield significant improvements in symptoms comparable to traditional therapy. |

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**5. Recent Trends & Developments**

- **Generative AI/LLMs in Clinical Settings:** Rule-based chatbots are being replaced by LLMs capable of nuanced, context-sensitive, empathetic conversations, improving the delivery of CBT exercises and therapeutic interventions.
- **Multimodal Data Fusion:** Fusion of text-based emotional state with objective biometric data (HR, sleep) improves accuracy of stress/mood prediction and recommendation relevancy.
- **Security and MLOps Maturity:** Adoption of robust CI/CD pipelines, automated monitoring, and Security-by-Design principles, including emerging federated learning practices, is becoming standard for sensitive healthcare AI applications.

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**6. Methodology / Action Plan (Workflow)**

**A. Data Ingestion & Transformation (ETL)**

- **Chat Data Ingestion:** User inputs captured via the React Native frontend and sent to backend microservices.
- **Wearable Data Ingestion:** APIs connect to third-party services (Apple Health / Google Fit) to pull HR, sleep, and activity metrics.
- **Real-Time Processing:** Raw data streams into Kafka, processed by lightweight consumers, and stored in MongoDB (Chat) and PostgreSQL (Biometrics / Profiles).

### B. Analytical Core Processing

- **NLP Pipeline:** Raw chat text is fed to a fine-tuned BERT model for Sentiment Score and Emotion Tagging (e.g., anxious, neutral, frustrated).
- **Biometric Processing:** Physiological data is analyzed for anomalies and trends (e.g., sudden drop in sleep quality, sustained elevated resting HR).
- **Multimodal Fusion:** A Bayesian model combines the NLP scores and the biometric indicators to generate a single, Personalized Wellness Index (PWI).

### C. Recommendation and Feedback Loop

- **Recommendation Engine:** The PWI triggers the recommendation engine, which queries the content library (meditations, journaling prompts, CBT exercises).
- **Front-end Delivery:** Suggested activities are presented on the mobile app/dashboard.
- **Continuous Retraining Loop (MLOps):** User engagement data (clicks, PWI changes) feeds back into the ML model via MLflow, enabling automated retraining cycles to improve personalization.

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## 7. Data Analysis Methods

| Aspect | Technique/Model | Tool/Platform | Rationale |
|---|---|---|---|
| Sentiment Analysis | Fine-tuned BERT or RoBERTa | TensorFlow / PyTorch | High accuracy for context-specific sentiment detection in conversational text. |
| Recommendation Engine | Collaborative Filtering (Hybrid Model) | Scikit-learn, Custom Python Scripts | Combines user profile similarity with PWI state for highly relevant content suggestions. |
| Physiological Analysis | Time-Series Smoothing, Statistical Process Control (SPC) | Pandas, NumPy | Detects statistically significant deviations from a user's baseline in HR and sleep data. |

| Aspect | Technique/Model | Tool/Platform | Rationale |
|---|---|---|---|
| Data Visualization | Interactive Charts / Graphs / Trends | React.js (D3.js or Recharts) | Provides longitudinal insights to users and clinicians. |
| Deployment / Monitoring | Containerization, CI/CD | Docker, Kubernetes, MLflow | Ensures reproducibility, scalability, and continuous performance tracking. |

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### 8. Plan of Work (Gantt-style Timeline)

| Phase | Activities and Milestones | Start Date | End Date | Responsibility |
|---|---|---|---|---|
| **Phase 1: Discovery & Architecture (2 Weeks)** | Finalize HIPAA/GDPR Data Governance Plan & Security Checklist | 27 Sep | 3 Oct | All Group (collaborative) |
| | Final System Architecture Blueprint (Microservices, Databases) | 4 Oct | 11 Oct | All Group (collaborative) |
| | Initial Cloud Infrastructure Setup (Compute, Storage) | 4 Oct | 11 Oct | All Group (collaborative) |
| **Phase 2: Core MVP Build (4 Weeks)** | Develop Chatbot API (Basic Request/Response) | 12 Oct | 19 Oct | All Group (collaborative) |
| | Frontend Mobile App (Login/Chat Screen) MVP | 12 Oct | 26 Oct | All Group (collaborative) |
| | Initial NLP Model Training and API Integration (Sentiment Detection) | 12 Oct | 26 Oct | All Group (collaborative) |
| | PoC: Wearable Data Integration (HR/Sleep) & Data Storage | 27 Oct | 8 Nov | All Group (collaborative) |
| **Phase 3: Integration & Testing (1.5 Weeks)** | MVP Recommendation Engine Logic Development (Fusion + Basic Recommendation) | 9 Nov | 15 Nov | All Group (collaborative) |

| Phase | Activities and Milestones | Start Date | End Date | Responsibility |
|---|---|---|---|---|
| | Final Frontend Dashboard (Visualization of PWI & Trends) | 9 Nov | 15 Nov | All Group (collaborative) |
| | FINAL MVP DEMO & Submission Documentation | 16 Nov | 20 Nov | All Group (collaborative) |

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**9. Feasibility Analysis**

**A. Technical Feasibility**

- **Verdict:** Highly feasible. Components (React, LLM APIs, MLOps, cloud tech) are mature; integration and compliance are the main challenge.
- **Risk:** Data normalization and integration across wearable APIs.
- **Mitigation:** Focus PoC on a single standardized platform (Google Fit / Apple Health).

**B. Time Feasibility**

- **Verdict:** Feasible for MVP by Nov 20; aggressive schedule.
- **Risk:** NLP model training or API mapping delays.
- **Mitigation:** Pre-trained BERT foundation + 2-week ML integration buffer.

**C. Economic (Cost) Feasibility**

- **Verdict:** Moderate–High cost for cloud and compute resources.
- **Mitigation:** Use serverless functions, spot instances, and minimal infra for MVP.

**D. Operational Feasibility**

- **Verdict:** Complex but manageable with strict protocols.
- **Mitigation:** MLOps pipelines ensure all deployments, data handling, and updates are traceable, auditable, and compliant.

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