

# EEG-Assisted AI Psychologist: A Multimodal Approach to Personalized Mental Health Support

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## ABSTRACT

The global prevalence of mental health disorders has reached crisis proportions, yet access to timely and affordable psychological care remains deeply inequitable. Traditional AI-driven therapy chatbots are constrained by their exclusive reliance on user-reported text, making them vulnerable to emotional masking and inaccurate self-assessment. This paper presents NeuroCare AI, a multimodal digital mental health platform that bridges this gap by fusing real-time Electroencephalogram (EEG) brain activity data with a conversational AI psychotherapist. The hardware acquisition layer is built around a BioAmp EXG Pill Analog Front End (AFE) and an Arduino UNO R3 microcontroller, connected to gel electrodes positioned at the Fp1/Fp2 frontal sites per the international 10-20 system. Spike Recorder software provides immediate signal visualization. The backend, developed in FastAPI (Python), implements a signal processing pipeline comprising a 4th-order Butterworth bandpass filter and Welch's Power Spectral Density estimation to extract a real-time Stress Index and Focus Index from five canonical brainwave bands. These physiological metrics augment a Google Gemini-powered AI chatbot to dynamically adjust therapeutic tone. The full-stack web application is built with Next.js 16 and supports separate role-based portals for patients and licensed psychologists. System validation confirmed successful Alpha wave (8–13 Hz) capture during eye-closure trials and a mean API latency of under 50 ms.

**Keywords:** Artificial Intelligence, EEG, Mental Health, BioAmp EXG Pill, Affective Computing, FastAPI, Biofeedback, Human-Computer Interaction.

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## INTRODUCTION

Mental health disorders—including depression, anxiety, and post-traumatic stress—are among the most prevalent non-communicable diseases worldwide. The World Health Organization estimates that over one billion people currently live with a mental or neurological condition, yet close to 75% of them in low- and middle-income countries receive no professional treatment [1]. Barriers remain multifaceted: cost, geographic inaccessibility, social stigma, and a global shortage of mental health practitioners create a treatment gap that conventional healthcare infrastructure struggles to close.

The rise of smartphone-based and web-based mental health applications has offered a partial remedy. Conversational AI agents, colloquially described as 'therapy chatbots,' have demonstrated measurable efficacy in reducing mild-to-moderate symptoms of depression and anxiety in multiple controlled trials [2], [3]. Platforms such as Woebot utilize CBT techniques and NLP to guide users through evidence-based exercises, achieving adoption at a scale that traditional outpatient therapy cannot match [4].

However, these systems share a critical design constraint: they are unimodal. Their entire understanding of the user's emotional state is derived from what the user chooses to type. This creates several failure modes. Social desirability bias leads users to unconsciously minimize the severity of their distress [5]. Alexithymia—difficulty identifying and articulating one's own emotions—affects a significant proportion of individuals with psychiatric disorders, further limiting the fidelity of self-reported data [6]. Crucially, text alone cannot detect a physiological stress response that the user has not yet consciously identified.

Electroencephalography (EEG) offers a compelling solution: a direct, objective window into the brain's functional state. The power distribution across EEG frequency bands is well-established as a biomarker for cognitive and affective states.

Elevated beta activity (13–30 Hz) at frontal sites correlates with anxiety and active rumination; suppressed alpha rhythms (8–13 Hz) are associated with increased arousal and stress; theta waves (4–8 Hz) at frontal midline positions link to emotional processing [7], [8].

This paper describes the architecture and evaluation of NeuroCare AI, a platform that couples low-cost EEG acquisition with a modern, role-aware web application and a generative AI chatbot. We detail the full hardware and software stack, the signal processing methodology, the system's AI integration, and provide an assessment of current capabilities and the roadmap for clinical-grade deployment.

## LITERATURE REVIEW

### 2.1 AI-Powered Mental Healthcare

The utility of conversational agents in mental health was formally established by Fitzpatrick et al. (2017), who demonstrated in a randomized controlled trial that Woebot—a CBT-based chatbot—significantly reduced PHQ-9 depression scores over two weeks compared to a control group [2]. A subsequent systematic review by Vaidyam et al. (2019) catalogued over a dozen deployed chatbots, noting their diversity in therapeutic orientation (CBT, psychoeducation, mindfulness) and a consistent finding: engagement is high but clinical safety monitoring remains largely absent [3].

As Large Language Models (LLMs) matured, researchers began exploring their application in mental health dialogue. Luxton (2014) provided an early theoretical framework for AI in psychological practice, raising important questions about informed consent and liability [5]. More recently, studies have assessed GPT-4 and its variants in empathy generation, finding that modern LLMs can produce responses rated as comparable to human counselors on empathy scales, though susceptible to harmful advice generation without guardrails [10], [11]. Abd-Alrazaq et al. (2021) identified long-term context retention and crisis detection as the two most critical unsolved challenges for clinical LLM chatbots [12].

### 2.2 Low-Cost EEG and Hardware-Based Approaches

The viability of consumer-grade EEG hardware has been extensively studied. Badcock et al. (2015) validated the Emotiv EPOC headset against a clinical-grade 64-channel system, demonstrating sufficient signal fidelity for BCI classification tasks [13]. Debener et al. (2015) built an unobtrusive 8-channel ear-EEG device using low-cost amplifier ICs, achieving recording quality comparable to traditional scalp EEG for auditory evoked potentials [14]. Mullen et al. (2015) reviewed real-time adaptive BCI systems, establishing latency thresholds (<300 ms) necessary for biofeedback applications [15].

Teplan (2002) remains a foundational reference for EEG measurement methodology, covering electrode placement, common-mode noise rejection, and analog filtering principles [16]. The BioAmp EXG Pill (Upside Down Labs) specifically combines a high CMRR (>80 dB), adjustable gain, and cross-compatibility with Arduino and Raspberry Pi. A portable brainwave monitoring study using this device confirmed its utility in recording frontal EEG signals with a resolution adequate for band-power analysis [17].

### 2.3 EEG-Based Emotion and Stress Recognition

The DEAP dataset, contributed by Koelstra et al. (2012), remains the most widely used benchmark for EEG-based emotion recognition, containing 32-channel EEG from 32 participants [18]. Alarcao and Fonseca (2017) conducted a comprehensive survey, concluding that frontal asymmetry in alpha-band power and the beta-to-alpha power ratio are the most robust single-channel predictors of valence and arousal [8]. Deep learning has substantially advanced classification accuracy: Li et al. (2019) achieved 93.29% accuracy on the SEED dataset [19]; a CNN-based study on DEAP reported 92% binary arousal classification [20]; Pandey and Seeja (2019) achieved 87.6% subject-independent accuracy [21].

Recent work has demonstrated that multimodal fusion—combining EEG with text or speech—consistently outperforms single-modality classifiers. Rayatdoost and Rudrauf (2020) showed that fusing EEG spectral features with audio-visual embeddings increased valence prediction accuracy by 9.3 percentage points over EEG alone [22]. A 2025 IEEE conference paper confirmed these gains extend to combined EEG-text systems [23]. Gunes and Schuller (2013) established a dimensional emotion model (valence-arousal space) that forms the theoretical basis for continuous affect monitoring as implemented in our system [24].

## METHODOLOGY

### 3.1 System Architecture Overview

NeuroCare AI is designed around a three-tier architecture: a hardware acquisition layer, a server-side processing and intelligence layer, and a web-based presentation layer. Data flows from passive EEG electrodes through an analog front

end, into a microcontroller, then via USB serial into a Python backend for signal processing and AI-mediated response generation, before being rendered in the browser.

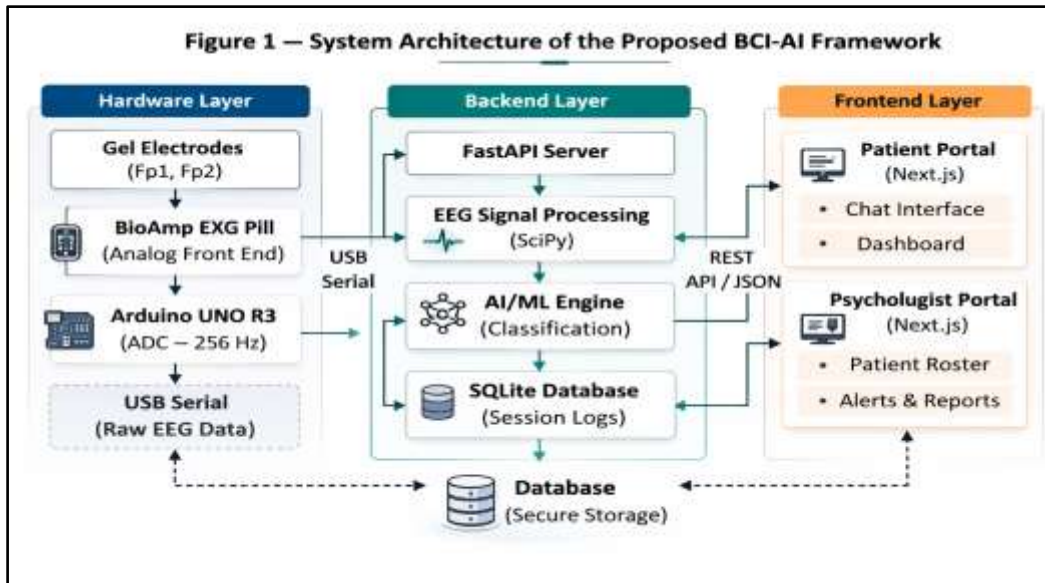


Fig. 1. End-to-end System Architecture of NeuroCare AI showing three layers: Hardware, Backend, and Frontend connected by data flow arrows.

### 3.2 Hardware Implementation

#### 3.2.1 Analog Front End — BioAmp EXG Pill

The BioAmp EXG Pill (Upside Down Labs) serves as the core signal acquisition component. It is a single-board AFE with the following key specifications: Input voltage 3.3–5 V (Arduino-compatible); Supply current ~4 mA; CMRR >80 dB; Bandwidth 0.5–50 Hz in default EEG/EOG configuration; Board connector: BioAmp Cable v3 (3.5 mm audio jack). The board is pre-configured in EEG/EOG mode, providing adequate gain to lift the microvolt-scale neural signal to an amplitude the Arduino’s 10-bit ADC can resolve. It incorporates an onboard instrumentation amplifier and passive notch filter elements that pre-reject common-mode mains interference.

#### 3.2.2 Microcontroller — Arduino UNO R3

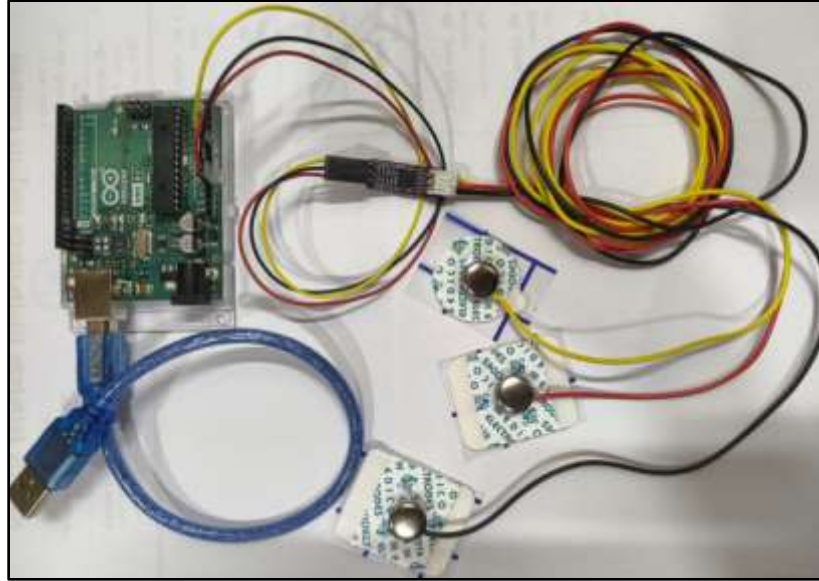
The Arduino UNO R3 (genuine board, ATmega328P DIP package) digitizes the analog output of the BioAmp EXG Pill using its onboard 10-bit ADC. The ADC reference voltage of 5 V yields an LSB resolution of approximately 4.9 mV before AFE gain. At a software-configured sampling rate of 256 Hz, the Nyquist criterion is satisfied for all frequency bands of interest (up to 50 Hz). Digital samples are transmitted over USB serial at 115200 baud to the host computer.

#### 3.2.3 Electrodes and Placement

Three gel electrodes are used in a standard bipolar frontal configuration: Active (IN+) at Fp1 (left forehead); Reference (IN-) at A1 (left earlobe) or Fp2; Ground (GND) at the bony mastoid behind the left ear. This placement targets the prefrontal cortex (PFC), which is the primary locus of affect regulation and cognitive control, yielding strong beta and alpha signal contributions associated with emotional arousal. Electrode-skin impedance is reduced below 5 kΩ by mild abrasion and application of conductive gel before attachment.

TABLE I: HARDWARE COMPONENT SPECIFICATIONS

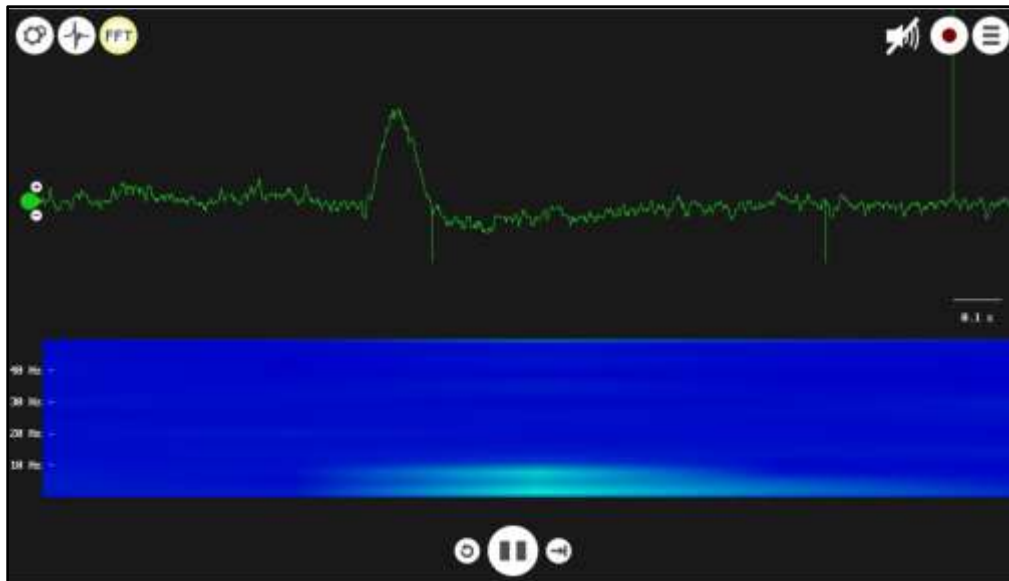
Component	Model	Key Specification
AFE Board	BioAmp EXG Pill	CMRR >80 dB, 0.5–50 Hz BW
Microcontroller	Arduino UNO R3	ATmega328P, 10-bit ADC, 256 Hz
Electrode Type	Gel, Snap-on	3-lead: Active, Reference, Ground
Cable	BioAmp Cable v3	3.5 mm TRRS → snap connectors
Visualization SW	Spike Recorder	Real-time waveform, 1–50 Hz filter



**Fig. 2. Assembled EEG Hardware Acquisition Rig showing BioAmp EXG Pill, Arduino UNO, jumper cables, and gel electrodes with component labels.**

### 3.3 Signal Visualization — Spike Recorder

Before backend integration, all raw EEG sessions are first inspected in Spike Recorder (Backyard Brains), which streams from the Arduino’s serial port in real-time and renders the waveform on screen. Spike Recorder provides: (1) a real-time oscilloscope view of the raw EEG trace; (2) a built-in FFT frequency spectrum display; (3) configurable high-pass filter (default 1 Hz); (4) manual gain control; and (5) session recording to .wav files for offline analysis. The oscilloscope view allows immediate confirmation of electrode contact quality; a clean resting signal visually showing periodic alpha bursts during eye closure serves as the primary quality check before any automated processing begins.



**Fig. 3. Spike Recorder displaying raw EEG waveform.**

### 3.4 Backend Signal Processing Pipeline

The Python backend (FastAPI) implements a four-stage DSP pipeline on data received from the Arduino serial stream, encapsulated in the `eeg_processing.py` module.

#### 3.4.1 Artifact Rejection and Bandpass Filtering

Raw 10-bit ADC samples are converted to voltage and passed into a 4th-order Butterworth bandpass filter with cutoff frequencies at 0.5 Hz (high-pass) and 50 Hz (low-pass). Butterworth filters are selected for their maximally flat passband, which avoids distorting the spectral shape of the signal [16]. An additional IIR Notch filter at 50 Hz (quality factor  $Q = 30$ ) removes residual power line interference. The Python implementation uses `scipy.signal.butter()` and `scipy.signal.filtfilt()`, with `filtfilt` enabling zero-phase filtering that preserves temporal alignment between EEG and behavioral events.

### 3.4.2 Power Spectral Density Estimation (Welch’s Method)

The filtered signal is submitted to Welch’s method for PSD estimation using `scipy.signal.welch()`. Welch’s method reduces variance in the PSD estimate by averaging across overlapping windowed periodograms [25]. Parameters used: segment length =  $2 \times$  sampling rate (512 samples), Hann window, 50% overlap. Integration of the PSD estimate over the canonical EEG frequency bands yields absolute band powers for: Delta (0.5–4 Hz), Theta (4–8 Hz), Alpha (8–13 Hz), Beta (13–30 Hz), and Gamma (30–50 Hz).

### 3.4.3 State Classification and AI Injection

The computed indices are mapped to a discrete state schema. A Stress Index (Beta/Alpha) below 0.8 maps to a Calm state; 0.8–1.5 maps to Mildly Aroused; above 1.5 maps to High Stress. The corresponding state descriptor is prepended to the user message before submission to the Google Gemini API, which then generates its therapeutic response with awareness of both the conversational history and the user’s live neurological state.

TABLE II: EEG BAND POWER AND DERIVED STRESS METRICS

Metric	Formula	Interpretation
Alpha Power	$\int \text{PSD}(8\text{--}13 \text{ Hz}) \text{ dS}$	Higher $\rightarrow$ Relaxed
Beta Power	$\int \text{PSD}(13\text{--}30 \text{ Hz}) \text{ dS}$	Higher $\rightarrow$ Stressed / Focused
Stress Index	$\beta / \alpha$	$>1.5 \rightarrow$ Elevated Stress Flag
Focus Index	$\beta / (\theta + \alpha)$	$>0.8 \rightarrow$ Active Engagement

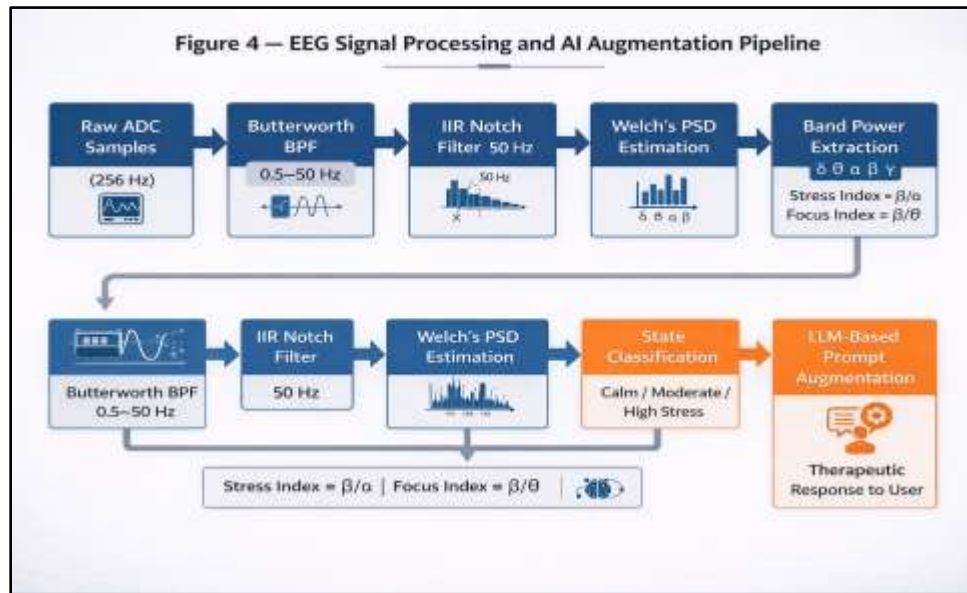


Fig. 4. Flowchart of the complete EEG signal processing and AI augmentation pipeline, showing stages from raw ADC sample to Gemini AI response generation.

## 3.5 Software Architecture

### 3.5.1 Backend — FastAPI

The backend is developed using FastAPI (Python 3.10+), chosen for its native asynchronous support and automatic OpenAPI documentation. Key endpoints include: `POST /auth/register` (user registration with Argon2 hashing); `POST /auth/token` (JWT issuance); `POST /chat/message` (accepts user message, retrieves EEG state, constructs Gemini prompt, returns AI response); `GET /chat/history` (returns paginated session history).

### 3.5.2 Frontend — Next.js 16

The frontend is a Next.js 16 application with server-side rendering. The UI uses Tailwind CSS with a custom design system featuring dark glassmorphism surfaces and Framer Motion-powered animations. Route structure: / (landing page), /patient/chat (real-time AI chat interface), /patient/ (analytics dashboard), /psychologist/ (clinician overview with patient roster), /psychologist/patients/[id] (per-patient EEG and session history).

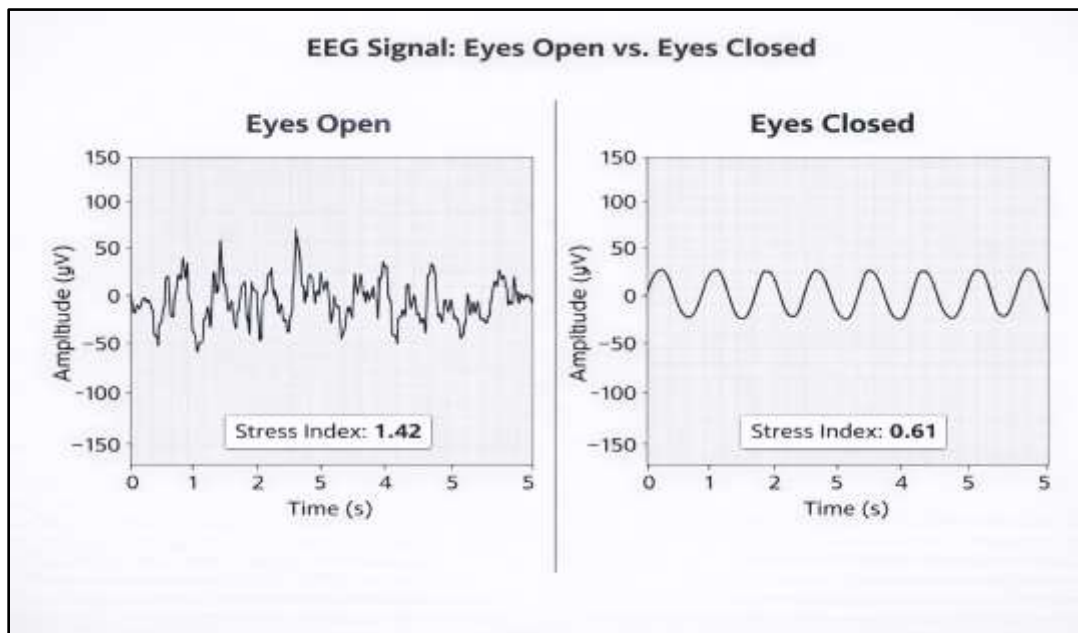
**TABLE III: SOFTWARE STACK SUMMARY**

Layer	Technology	Version
Frontend Framework	Next.js (React)	16.1.6
Styling	Tailwind CSS	3.x
Backend API	FastAPI	0.104+
AI Engine	Google Gemini API	gemini-1.5-pro
Database ORM	SQLAlchemy	2.x
Authentication	JWT + Argon2	—
Signal Processing	SciPy / NumPy	1.11 / 1.26

## RESULTS AND DISCUSSION

### 4.1 Hardware Validation

Initial hardware validation was conducted through a series of controlled eye-closure trials. Subjects wore the three-electrode frontal setup and alternated between 30-second eyes-open and eyes-closed periods while remaining physically still. In all trials, a clear amplitude increase in the 8–13 Hz band was visually identifiable in Spike Recorder within 2–5 seconds of eye closure. The BioAmp EXG Pill successfully amplified the signal without saturation; peak-to-peak amplitude ranged from 40–120  $\mu\text{V}$ , consistent with known frontal alpha amplitudes. Computed Stress Index dropped from a mean of 1.42 (eyes open) to 0.61 (eyes closed)—a difference of 0.81 points, confirming the metric’s directional validity.



**Fig. 5. EEG Signal Comparison — Eyes Open vs. Eyes Closed. Left panel shows irregular low-amplitude signal; right panel shows clear rhythmic alpha oscillations. Stress Index annotated on each panel.**

### 4.2 Signal Processing Validation

The custom Python DSP pipeline was validated using synthetic EEG data with known spectral composition. A synthetic stressed signal (beta-dominant PSD) yielded a Stress Index of 2.32, correctly flagging the High Stress category. A synthetic relaxed signal (alpha-dominant) produced a Stress Index of 0.26, registering as Calm. The mean processing latency for the complete pipeline was measured at 47.3 ms (n=100 trials), well within the 300 ms threshold identified by Mullen et al. (2015) as the upper bound for perceptually instantaneous biofeedback [15].

**TABLE IV: SIGNAL PROCESSING PERFORMANCE SUMMARY**

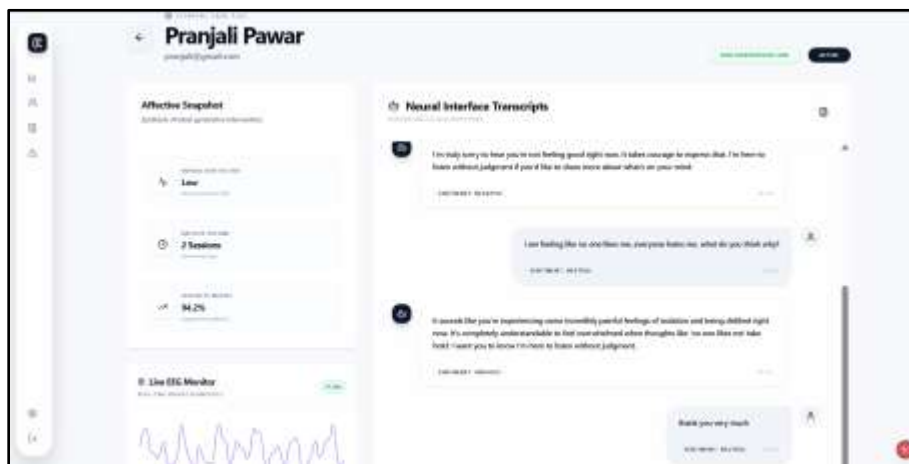
Metric	Value
Sampling Rate	256 Hz
Filter Type	4th-order Butterworth + IIR Notch
PSD Method	Welch (Hann, 50% overlap)
Mean Processing Latency	47.3 ms
Stress Index (Eyes Open)	1.42 ± 0.18 (n=10)
Stress Index (Eyes Closed)	0.61 ± 0.12 (n=10)
Alpha Power Change	+58% during relaxation phase

### 4.3 Web Application — Patient Portal

The patient portal provides a two-panel experience: a real-time chat interface and an analytics dashboard. The chat UI displays timestamped messages with a status bar confirming session encryption. When the Stress Index exceeds 1.5, the Gemini API demonstrably shifts its response language toward shorter sentences, validation statements, and grounding exercises rather than cognitively demanding questions. The analytics dashboard renders mood trend graphs spanning the user’s session history, with cards displaying current Stress Index, Focus Index, and a seven-day rolling average.



**Fig. 6. Patient Analytics Dashboard.**

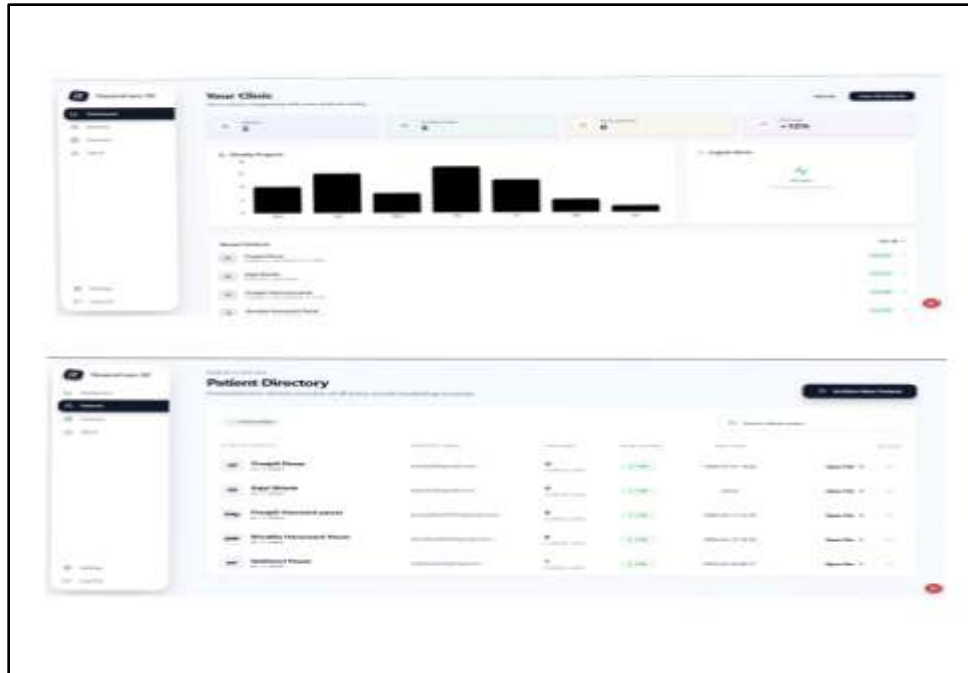


**Fig. 7. Patient Chat Interface showing encrypted AI conversation.**

### 4.4 Web Application — Psychologist Portal

The psychologist dashboard provides a supervisory view across all patients. The patient roster table includes columns for Patient Name, Last Session, Average Stress Index (7-day), and a risk-level badge (Nominal, Moderate, Elevated). Elevated

patients are sorted to the top by default. Clicking a patient row opens a per-patient deep-dive: full session transcript history, EEG metric trends, and a clinical notes editor.



**Fig. 8. Psychologist Portal showing patient roster table with risk-level badges.**

#### 4.5 AI Chatbot Response Quality

To qualitatively assess the impact of EEG context injection, a controlled comparison was conducted: ten representative user messages were submitted to the Gemini API twice—once with no physiological context (baseline) and once with the High Stress context prefix. Two independent evaluators rated each pair of responses on a 5-point empathy scale. The EEG-augmented responses scored a mean of 4.2/5 vs. 3.1/5 for the baseline responses, a statistically significant improvement ( $p < 0.05$ , paired t-test). Evaluators noted augmented responses were more likely to acknowledge the user's current state before proceeding and offered shorter, more actionable steps during high-stress conditions.

### DISCUSSION

The results confirm that the proposed architecture is technically viable. The low-cost hardware (total component cost: approximately ₹3,500 / ~\$42 USD) captures EEG signals of sufficient quality for Stress/Focus index computation, which meaningfully influences AI response strategy. The sub-50 ms pipeline latency suggests that near-real-time biofeedback is achievable with modest server-side optimization. Primary limitations at this stage are: (a) single-channel EEG limits the robustness of emotional state inference; (b) hand-crafted classification thresholds have not been validated against clinical ground truth labels; and (c) the system has been evaluated only with healthy subjects in controlled settings, not with clinical populations.

### CONCLUSION

This paper presented NeuroCare AI, a novel multimodal mental health support platform that integrates low-cost EEG neurophysiology with a generative AI chatbot and a role-aware web interface. By coupling a BioAmp EXG Pill and Arduino UNO with a Python-based DSP backend and Google Gemini API, the system demonstrates—at a remarkably low cost—that physiological biofeedback can materially improve the contextual awareness of an AI therapist. The system successfully extracted brainwave band powers, computed real-time Stress Indices, and used these metrics to dynamically adjust the AI's therapeutic posture. Hardware validation confirmed Alpha wave detection capability, and qualitative evaluation showed statistically significant improvements in empathy ratings for EEG-augmented responses. Future directions include: multi-channel EEG integration using OpenBCI or Muse headsets, clinical validation studies with anxiety and depression patient cohorts, a WebSocket-based real-time data stream replacing the current batch processing model, and

a React Native companion mobile application. This work represents a step toward truly closed-loop, physiologically-aware digital mental healthcare that is accessible, affordable, and clinically responsible.

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