

# Mental Health Monitoring and Relaxation Companion

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**ABSTRACT** - In today's fast-paced world, mental health has become increasingly critical yet often overlooked. Stress, anxiety, and depression affect millions globally, and early detection can prevent serious health complications. This paper presents **MindEase**, an innovative IoT-based system that monitors mental health in real-time using physiological biosensors and provides intelligent relaxation feedback. The system integrates four biosensors—ECG (Electrocardiogram), pulse, temperature, and GSR (Galvanic Skin Response)—connected to a NodeMCU (ESP8266) microcontroller for data acquisition. The collected data is transmitted to ThingSpeak, an IoT cloud platform, for real-time visualization and storage. A Python-based software interface processes the sensor data, classifies stress levels, and automatically triggers personalized relaxation interventions such as soothing music, meditation videos, and medical consultation alerts. The multi-modal sensor approach demonstrates high accuracy in stress detection compared to single-sensor systems, making it a practical solution for students, professionals, and individuals managing daily stress. Testing confirmed reliable operation across various physiological conditions, establishing MindEase as a comprehensive mental wellness companion combining hardware, IoT connectivity, and intelligent software analysis.

**Keywords:** Mental Health Monitoring, IoT, Biosensors, Stress Detection, ECG, GSR, NodeMCU, ThingSpeak, Python, Cloud Computing, Wearable Health Systems, Biofeedback.

## 1. INTRODUCTION

### 1.1 Background and Motivation

Mental health disorders are among the leading causes of disability worldwide, affecting an estimated 1 billion people. Unlike physical illnesses, mental stress is silent and accumulates gradually, often going undiagnosed until it reaches critical levels. The World Health Organization reports that over 280 million people suffer from depression, and millions more experience chronic anxiety and stress-related conditions. With the rising demands of modern life—academic pressure, work stress, financial concerns, and social challenges—the need for accessible, continuous mental health

monitoring has never been greater.

Traditional mental health assessment relies on periodic clinical visits, self-reported questionnaires, or retrospective interviews, all of which are time-consuming, subjective, and unable to capture real-time physiological changes. Our body, however, continuously communicates its stress state through physiological signals. When stressed, the sympathetic nervous system activates, leading to measurable changes in heart rate, blood pressure, skin conductivity, and body temperature. By monitoring these parameters continuously, we can detect stress early and intervene before it escalates into serious mental health conditions.

### 1.1 PROBLEM STATEMENT & OBJECTIVES

Current mental health monitoring systems suffer from several limitations:

#### **Lack of Real-Time Monitoring:**

Most assessments are sporadic and do not capture continuous physiological changes throughout the day.

#### **Inaccessibility:**

Mental health services are often expensive, geographically limited, and stigmatized in many communities.

#### **Inaccuracy of Self-Assessment:**

People often underestimate or deny their stress levels, leading to delayed intervention.

#### **Absence of Integrated Feedback:**

Existing systems detect stress but rarely provide immediate, personalized relaxation support.

There is a critical need for an affordable, non-invasive, and easily accessible system that can continuously monitor physiological markers of stress and provide timely interventions.

### 1.3 Proposed Solution: MindEase System

MindEase addresses these challenges by creating an integrated platform that combines physiological monitoring, cloud-based analytics, and intelligent feedback generation. The system detects stress through multiple biosensors, analyzes the data using IoT connectivity, and automatically provides personalized relaxation responses.

### 1.4 System Objectives

The main objectives of the MindEase system are:

1. **Design and develop** a non-invasive biosensor-based system for real-time mental health monitoring capable of detecting stress levels in individuals.
2. **Integrate IoT technology** using NodeMCU and ThingSpeak for seamless data collection, secure cloud storage,

and remote visualization of physiological parameters.

3. **Develop intelligent software** using Python to process raw sensor signals, filter noise, and classify stress states

into normal, moderate, and high categories.

4. **Implement automated relaxation feedback** that triggers music, meditation guidance, or medical alerts based on detected stress levels.

5. **Ensure system reliability and accessibility** for daily use by students, professionals, and individuals managing stress without professional intervention.

### 1.5 Scope and Significance

MindEase can be deployed in educational institutions, workplaces, hospitals, and personal homes. It provides:

- **Early stress detection** for prevention-focused healthcare
- **Continuous monitoring** without clinical visits
- **Personalized feedback** adapted to individual stress patterns
- **Cost-effective solution** compared to traditional mental health interventions
- **Remote accessibility** for underserved populations

This system contributes to the emerging field of digital mental health, promoting emotional well-being and supporting preventive healthcare in daily life

## 2. LITERATURE REVIEW

### 2.1 Physiological Stress Detection

Research in affective computing and psychophysiology confirms that stress produces measurable physiological changes. Picard's foundational work on "Affective Computing" established that emotions and stress states correlate with physiological signals including heart rate, skin conductivity, and body temperature. Healey and Picard's study on detecting stress during real-world driving demonstrated that multi-modal sensor fusion significantly improves stress detection accuracy compared to single-parameter monitoring.

Heart Rate Variability (HRV)—the variation between consecutive heartbeats—has emerged as a highly reliable stress indicator. Research shows that HRV decreases during stress as the sympathetic nervous system dominates, while relaxation increases HRV. This relationship is so consistent that HRV biofeedback is now an accepted therapeutic technique for stress management.

Electrodermal Activity (EDA), measured through Galvanic Skin Response (GSR), reflects sympathetic nervous system activation through skin conductivity changes during emotional arousal. Poh's study validated that GSR provides continuous, unobtrusive measurement of stress levels suitable for wearable applications.

### 2.2 Multi-Modal Biosensor Systems

A critical finding in stress monitoring research is that combining multiple biosensors significantly outperforms single-sensor approaches. Can, Arnrich, and Ersoy's

comprehensive survey of stress detection using smartphones and wearable sensors concluded that integrating ECG, GSR, temperature, and pulse data increases detection accuracy to 85-95%, compared to 65-75% for single sensors. This multi-

modal approach reduces false positives from individual sensor noise and captures the complexity of physiological stress responses.

Similarly, Shu's review of emotion recognition using physiological signals confirmed that ECG, GSR, and temperature together provide robust stress classification across diverse populations and scenarios.

### 2.3 Internet of Things in Health Monitoring

IoT technology has revolutionized healthcare by enabling continuous, remote monitoring. Wang et al.'s StudentLife project demonstrated that smartphone and wearable sensors connected to cloud platforms can effectively track behavioral and emotional patterns of college students in real-time. This work proved the feasibility of large-scale, non-intrusive health monitoring.

Zheng's review on unobtrusive sensing for health informatics highlighted how microcontrollers like NodeMCU can efficiently collect physiological data and transmit it to cloud platforms for analysis and visualization. The combination of wearable sensors, IoT connectivity, and cloud storage enables scalable, accessible health monitoring systems.

### 2.4 Cloud Platforms and Real-Time Data Processing

Research shows that cloud-based health systems provide significant advantages: remote access, real-time visualization, data security, and the ability to apply machine learning algorithms for pattern recognition. Studies on IoT health monitoring platforms confirm the reliability and efficiency of services like ThingSpeak for healthcare applications.

### 2.5 Feedback and Behavioral Intervention

While stress detection has advanced significantly, providing effective interventions remains underexplored. Lehrer and Gevirtz's research on HRV biofeedback proved that real-time physiological feedback enables individuals to consciously regulate stress through breathing and relaxation. However, most systems focus on detection without intervention.

Sano and Taylor's work on identifying physiological markers and modifiable behaviors demonstrated that combining stress detection with personalized recommendations (meditation, exercise, music) significantly improves user engagement and health outcomes.

### 2.6 Research Gap

The literature reveals that:

1. Most existing systems prioritize stress detection over intervention.
2. Few systems integrate all four key physiological parameters (ECG, GSR, temperature, pulse).
3. Limited research combines IoT connectivity, cloud analytics, and automated biofeedback in a single, affordable platform.
4. Accessibility to such systems remains limited in developing countries.

MindEase addresses these gaps by creating an integrated platform that combines multi-modal sensing, cloud connectivity, and intelligent relaxation feedback for accessible, continuous mental health monitoring.

## 3. SYSTEM ARCHITECTURE AND METHODOLOGY

### 3.1 System Overview

MindEase operates through four integrated components:

**Data Acquisition Layer:** Four biosensors capture physiological signals continuously.

**Processing and Communication Layer:** NodeMCU (ESP8266) microcontroller collects, processes, and transmits data via Wi-Fi.

**Cloud Analytics Layer:** ThingSpeak platform stores, visualizes, and manages data securely.

**Feedback and User Interface Layer:** Python application analyzes data and provides real-time relaxation guidance.

## 3.2 Hardware Components

### 3.2.1 ECG Sensor

The ECG (Electrocardiogram) sensor measures the electrical activity of the heart. It works through three electrodes placed on the chest, detecting the minute electrical signals generated during each heartbeat (typically 0.5-5 millivolts). The sensor includes:

- **Instrumentation amplifier:** Amplifies weak biopotential signals
- **Filtering circuits:** Removes noise from muscle movement and electrical interference
- **Lead-off detection:** Alerts if electrodes disconnect

From ECG data, the system derives:

- **Heart Rate (HR):** Beats per minute
- **Heart Rate Variability (HRV):** Time variation between consecutive beats (indicates stress level)
- **Heart Rhythm:** Pattern of contractions (detects arrhythmias)

**Stress Correlation:** Stress causes sympathetic nervous system activation, increasing HR and decreasing HRV. Low HRV typically indicates stress or fatigue.

### 3.2.2 GSR Sensor (Sweat/Electrodermal Activity Sensor)

The GSR sensor measures skin conductivity, which increases when sweat glands activate during emotional arousal. The sensor detects:

- **Electrolyte concentration:** Sodium, potassium changes in sweat
- **Cortisol levels:** The primary stress hormone, elevated in sweat during anxiety
- **Skin conductivity:** Direct measure of sympathetic nervous system activation

**Stress Correlation:** GSR responds rapidly to stress onset and provides continuous, real-time stress indication. It is highly sensitive and shows minimal lag compared to other sensors. Uses photoplethysmography (PPG) technology with an integrated LED and photodetector. It detects changes in blood volume with each heartbeat by measuring reflected light intensity from blood beneath the skin.

**Parameters Measured:**

- **Pulse rate (BPM):** Directly correlates with heart rate

- **Pulse strength:** Indicates cardiovascular response intensity

- **Pulse regularity:** Detects rhythm abnormalities

**Stress Correlation:** Sustained high pulse rate and irregular rhythm indicate stress. Combined with ECG data, pulse provides redundancy and increases detection reliability.

### 3.2.3 Temperature Sensor (LM35 or DS18B20)

Measures skin surface temperature, which increases during stress due to increased blood circulation and metabolic activity. Output voltage is linear with temperature (10 mV per °C for LM35).

**Parameters Measured:**

- **Skin temperature:** Normal baseline ~32-34°C; rises 0.5-2°C during stress
- **Temperature stability:** Fluctuations indicate physiological changes

**Stress Correlation:** Elevated body temperature correlates with sympathetic nervous system activation, indicating stress or anxiety.

### 3.2.4 NodeMCU (ESP8266) Microcontroller

The central processing unit connects all sensors through analog-to-digital converters (ADC), processes signals, and transmits data to the cloud via Wi-Fi. Key specifications:

- **Processor:** 32-bit Tensilica L106
- **RAM:** 160 KB
- **ADC:** 10-bit, 0-1024 range
- **Wi-Fi:** 802.11 b/g/n
- **Power:** 3.3V, ~80 mA average current

## 3.3 Software Implementation

### 3.3.1 Firmware (Arduino IDE C++)

The NodeMCU firmware:

1. **Reads analog inputs** from all four sensors at 10-Hz sampling rate
2. **Applies preliminary filtering** to remove high-frequency noise
3. **Normalizes data** to 0-100 scale for comparability
4. **Transmits to ThingSpeak** every 2 seconds via HTTP request with API key
5. **Stores local timestamp** for correlation analysis parameters. Cloud Platform (ThingSpeak)

ThingSpeak provides:

- **Real-time data storage** with timestamps
- **Automatic visualization** through graphs and dashboards
- **Data retention** for long-term analysis
- **API access** for Python application to retrieve data
- **Field segregation** for each sensor parameter

### 3.3.2 Python Analysis Application

The Python application running on a PC performs:

**Data Retrieval:**

```
text
import requests
# Fetch latest 100 data points from ThingSpeak response =
requests.get(f"https://api.thingspeak.com/channels/{CH
ANNEL_ID}/feeds.json?results=100&api_key={API_KEY}")
data = response.json()
```

**Signal Processing:**

- **Butterworth filtering** (low-pass at 0.5 Hz) removes motion artifacts
- **Z-score normalization** standardizes parameters across individuals
- **Moving average** (10-second window) smooths noise while preserving stress onset

**Stress Classification Algorithm:**

The system computes a **Stress Index (SI)** combining all four parameters:

$$SI = (0.35 \times HR\_deviation) + (0.30 \times HRV\_deviation) + (0.20 \times GSR\_deviation) + (0.15 \times Temp\_deviation)$$

Where deviation = (current\_value - baseline) / baseline

**Classification:**

- **Normal:** SI < 20 (baseline state)
- **Moderate Stress:** SI 20-50 (elevated sympathetic activity)
- **High Stress:** SI > 50 (severe stress requiring intervention)

**Baselines** are automatically calibrated during the first 5 minutes of system startup by averaging readings from a calm period.

**Feedback Mechanism**

Upon stress detection, the system automatically:

1. **Moderate Stress (SI 20-50):**
  - Plays calming instrumental music for 5 minutes
  - Suggests 3-minute breathing exercise (4-7-8 technique)
  - Displays relaxation tips on-screen
- **High Stress (SI > 50):**
  - **Initiates 10-minute meditation guidance**
  - Recommends yoga stretches specific to stress relief
  - Alerts user to contact healthcare provider if sustained for >15 minutes
  - Logs event with timestamp for trend analysis

**3.4 Data Flow**



1. A FAISS (Facebook AI Similarity Search) vector index is created to store these vectors.
2. FAISS enables:
  - a. High-speed similarity search
  - b. Efficient retrieval of the most relevant chunks during question answering

**4. RESULTS AND PERFORMANCE ANALYSIS**

**4.1 Data Collection and Testing**

The MindEase system was tested on 20 volunteer subjects (ages 18-35) with various stress levels—students during exams, professionals during work deadlines, and individuals in relaxed states. Each subject was monitored for 30 minutes.

**4.2 Sensor Performance**

**4.2.1 ECG Sensor Results**

- **Accuracy:** ±2 bpm compared to clinical ECG monitors
- **Response time:** <500 ms to stress onset
- **Signal-to-noise ratio:** >20 dB after filtering
- **HRV sensitivity:** Successfully detected stress-induced HRV reduction (30-40% decrease during stress vs. baseline)

**4.2.2 GSR Sensor Results**

- **Response time:** <1 second to stress stimulus (fastest sensor)
- **Discrimination:** Successfully separated normal (baseline conductivity 0.5-2 μS) from stress (3-10 μS increases)
- **False positives:** <5% when accounting for physical activity baseline

**4.2.3 Pulse Sensor Results**

- **Accuracy:** ±3 bpm vs. ECG reference
- **Reliability:** Consistent readings across skin tone variations
- **Stability:** <2% variance over 30-minute continuous measurement

**4.2.4 Temperature Sensor Results**

- **Sensitivity:** Detected 0.5°C changes during stress
- **Response latency:** 2-3 minutes (slowest parameter, reflects metabolic changes)
- **Baseline variability:** ±0.3°C across different body locations

**4.3 Multi-Modal Stress Detection**

**Accuracy Comparison across detection approaches:**

- **ECG only:** 72% accuracy, 15% false positives
- **GSR only:** 78% accuracy, 12% false positives
- **Multi-modal (all 4): 89% accuracy, 4% false positives**

The multi-modal approach significantly outperformed single-sensor methods, confirming literature findings that sensor fusion improves reliability.

**4.4 Cloud Connectivity Performance**

- **Data transmission success rate:** 99.7% (1-2 failed uploads per 1000 attempts)
- **Average upload latency:** 1.2 seconds
- **Data retrieval from ThingSpeak:** <500 ms for 100 data points
- **System uptime:** 99.2% over 30-day test period

#### 4.5 User Interface and Feedback Effectiveness

##### Subjective user feedback (n=20, 5-point scale):

- Ease of setup: 4.6/5
- Interface intuitiveness: 4.4/5
- Comfort of sensors: 4.2/5
- Usefulness of feedback: 4.5/5
- Likelihood to continue using: 4.3/5

##### Objective feedback impact:

- 85% of users reported feeling calmer after music/meditation (subjective rating increase of 2-3 points)
- Average stress index reduction post-intervention: 35-45%
- Users appreciated real-time awareness of stress levels (previously unaware in 60% of cases)

#### 4.6 System Limitations

1. **Sensor placement sensitivity:** GSR readings vary significantly with electrode placement; requires user training
2. **Motion artifacts:** High physical activity produces false stress indicators; distinguishing exercise-induced HR from stress requires context
3. **Individual variability:** Baseline parameters differ widely across individuals; system requires 5-minute calibration
4. **Environmental factors:** Room temperature affects skin temperature readings; requires temperature-normalized analysis
5. **Feedback latency:** Python processing adds 2-3second delay between stress detection and feedback initiation

#### 4.7 Discussion

The results demonstrate that MindEase successfully integrates multiple physiological parameters for reliable, real-time stress monitoring. The 89% detection accuracy compares favorably with existing research systems (literature reports 85-95% for multi-modal approaches). The fast response time of GSR, combined with the stability of ECG and pulse, creates a robust system resistant to individual sensor failures.

The high user satisfaction scores indicate that the system successfully translates technical capabilities into practical, user-friendly monitoring. The automatic feedback mechanism proved effective, reducing stress indices by 35-45% within 3-5 minutes of intervention—comparable to structured breathing exercises.

However, the system's reliance on consistent sensor contact and proper calibration suggests the need for improved user onboarding and potentially semi-rigid sensor housings for deployment as a commercial product.

### 5. IOT CLOUD INTEGRATION DETAILS

#### 5.1 ThingSpeak Channel Configuration

Each physiological parameter is stored in a separate field:

- **Field 1:** ECG (raw ADC value, 0-1024)
- **Field 2:** Heart Rate (bpm, derived from ECG)
- **Field 3:** Pulse Rate (bpm)
- **Field 4:** GSR (skin conductance,  $\mu$ S)
- **Field 5:** Temperature ( $^{\circ}$ C)
- **Field 6:** Calculated Stress Index (0-100 scale)

#### 5.2 Data Security

- **API Key:** Unique write key protects from unauthorized uploads
- **HTTPS connection:** Encrypts data in transit
- **Cloud storage:** ThingSpeak maintains 15-day data

history

- **User authentication:** Password-protected Python dashboard prevents unauthorized access

#### 5.3 Remote Monitoring Capability

Authorized users can access live dashboards from any internet-connected device, enabling:

- Family members to monitor loved ones
- Healthcare providers to review patient trends
- Researchers to collect population-scale stress data

### 6. CONCLUSION

MindEase successfully demonstrates an integrated approach to continuous, accessible mental health monitoring through the combination of:

1. **Multi-modal biosensing** using ECG, pulse, temperature, and GSR sensors
2. **IoT cloud connectivity** enabling real-time data visualization and remote access
3. **Intelligent data analysis** using Python-based algorithms for stress classification
4. **Automated biofeedback** providing immediate, personalized relaxation interventions

Testing with 20 subjects over 30 days confirmed:

- **89% accuracy** in stress level classification
- **<1 second response time** for stress detection
- **99.7% cloud connectivity** reliability
- **4.3/5 average user satisfaction**
- **35-45% average stress reduction** following feedback interventions

The system addresses critical gaps in existing mental health monitoring by providing affordable, continuous, non-invasive stress tracking with integrated relaxation support. This work contributes significantly to the emerging field of digital mental health, supporting preventive healthcare and promoting emotional well-being.

### 7. FUTURE WORK AND ENHANCEMENTS

1. **Mobile Application:** Develop Android/iOS apps for portability and on-the-go monitoring
2. **Machine Learning Integration:** Implement neural networks to personalize stress thresholds and feedback based on individual patterns
3. **Extended Sensor Array:** Add respiration rate, blood oxygen ( $SpO_2$ ), and EEG signals for more comprehensive mental state assessment
4. **Long-Term Trend Analysis:** Collect 6-12 month data to identify chronic stress patterns and predict high-risk periods
5. **Integration with Therapy:** Connect with licensed mental health professionals for alert escalation in severe cases
6. **Wearable Form Factor:** Miniaturize sensors into a wristband or chest patch for seamless daily use
7. **Gamification:** Incorporate challenges and rewards to encourage consistent engagement with relaxation exercises

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