

SerenePulse: A Web App Pipeline for Real-time Physiological Monitoring Using rPPG and OpenAI LLMs

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I'm an Assistant Professor of Software Engineering and the director of the AIET lab in the College of Computing and Software Engineering at Kennesaw State University. With a Ph.D. in Computer Science and prior experience as a software engineer in the industry, my interest in both academic and research activities has laid the foundation to work on advancing educational technologies and pedagogical interventions.

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Abstract

With 15% of working-age adults facing mental disorders and an annual loss of US\$ 1 trillion in the world due to impaired productivity from depression and anxiety, the necessity for real-time emotional and physiological monitoring is paramount [1]. As similar levels of stress and mental health disorders are found among engineering students, mental health management is imperative in engineering education [2]. However, the high costs associated with mental health management tools, the necessity for additional gadgets, and rare usage among students pose significant barriers to widespread adoption and utilization in engineering education [3], [4]. In this study, we examine the integration of Remote Photoplethysmography (rPPG), a wireless stress measurement technology for real-time physiological monitoring by detecting light intensity variations on the skin. By advanced rPPG signal processing, Heart Rate Variability (HRV) metrics like Standard Deviation of Normal-to-Normal Intervals(SDNN), Root Mean Square of Successive Differences(RMSSD), and the Low-Frequency / High-Frequency Ratio(LF/HF) are calculated to offer stress insights. Our results resulted in an accuracy of 92% as validated with the ground truth dataset. Moving forward, we aim to enhance performance and deploy an app for widespread, low-cost access to stress management and monitoring.

Index Terms

Engineering education, stress reduction, relaxation practices, heart rate variability, Heart Coherence, Remote photoplethysmography, rPPG, LLM, GPT-4, RAG.

INTRODUCTION

Engineering education, known for its rigorous academic demands, mirrors the broader workplace environment where stress significantly impacts health and productivity. Stress is the Health Epidemic of the 21st Century [5]. Annually, stress-related factors contribute to approximately 2.8 million worker deaths globally, emphasizing the critical need for stress management in high-pressure fields [6]. In the United States, the pervasive influence of workplace stress is evident, with 76% of workers acknowledging its adverse effects on personal relationships and a staggering 66% experiencing sleep deprivation due to job-related stress [7]. Furthermore, the economic toll of stress, through factors such as employee disengagement, extends to an estimated annual global cost of \$7.8 trillion, underlining the substantial impact on both individual well-being and economic stability [8].

Stress, primarily originating from interpersonal interactions and the environment, is viewed as a multifaceted phenomenon encompassing negative emotions, cognitive dissonance, behavioral reactions, and physiological changes [9]. Stressors, such as peer pressure, parental expectations, and financial constraints, on top of academic pressure, can cause behavioral, cognitive, and psychological issues and can affect the GPA [10]. The stress hormone cortisol is released in higher quantities during stress, impacting various physiological functions such as impairing cognitive performance (problem-solving, and decision-making), thyroid function (irritability, anxiety, and memory loss), and increasing blood pressure (obscurity and hypertension) [11]. Just as diabetic patients routinely monitor blood sugar levels to manage their health, engineering students can similarly benefit from monitoring their stress levels to maintain their mental well-being and enhance academic productivity.

Recent advancements in technology have led to innovative methods for monitoring stress levels that are applicable in higher education. Wearable devices like smartwatches, fitness trackers, and other smart health services utilize

various physiological signals such as rPPG data for stress monitoring as shown in table I. These fitness devices generally calculate stress levels score from heart rate, physical exertion, sweat, and sleep data. The cost of wearable devices like Apple Watch, WHOOP, and Fitbit can be a significant barrier for college students, limiting their access to stress monitoring. Additionally, these devices require consistent usage to provide accurate data, and any change in users or forgetfulness in wearing them can disrupt the continuity of stress level monitoring. In contrast, remote rPPG technology offers a more accessible alternative. It utilizes common devices like webcams and smartphones, which are readily available to most engineering students. This technology not only benefits individual users but can also be advantageous for organizations seeking to monitor group stress levels.

Make	Metrics
Polar H10	ECG-based heart rate monitoring, detailed during physical activity [12].
Garmin Forerunner 255	HRV, recovery status, GPS tracking, AI-driven coaching, various health metrics [12].
Fitbit Inspire 3	Continuous heart rate monitoring, sleep performance, workout stats, HRV analysis [12].
Apple Watch Series 8	ECG sensor, HRV trends, sleep and activity tracking, health app integrations [13].
Whoop	Detailed sleep monitoring, lifestyle habit tracking, HRV trends, recovery scores [14].
EliteHRV	Comprehensive HRV analytics (RMSSD, SDNN, PNN50, LF/HF ratio) [14].

TABLE I: HRV metrics [15]

Heart Rate Variability(HRV) is a measure of the variation in time between successive heartbeats. It is a widely recognized non-invasive marker for assessing the balance between sympathetic and parasympathetic nervous system activities [16]. rPPG is a wireless method for measuring heart rate variability (HRV) using a digital camera. rPPG has seen significant advancements, particularly in algorithmic development for pulse extraction from facial videos. In the realm of remote rPPG, face detection tracking is pivotal for accurate HRV analysis. Viola-Jones algorithm, a cascade of simple Haar-like features, used this face detection technology to sift through frames, identifying face-like patterns for efficient real-time rPPG face detection [17]. Skin segmentation, especially focusing on the forehead region, is a critical step, as this area offers a high signal-to-noise ratio, making it ideal for capturing subtle blood flow changes [18]. The extraction of the rPPG signal predominantly leverages the green channel of the RGB color space, a choice empirically validated for its heightened sensitivity to blood volume variations under the skin [19]. Even more, the integration of the rPPG-Toolbox system enhances the accuracy of the algorithm, especially in countering motion artifacts and variable lighting, a significant advancement in the field [20]. This toolbox's use of unsupervised and supervised learning models benchmarked against public datasets, ensures wide applicability across diverse environmental conditions and skin types [20]. In this study, we used such advancements to improve the efficacy and accuracy of rPPG technologies in non-invasive stress monitoring.

Furthermore, as a response to detected high stress, there are several practices suitable for engineering students to bring stress under control as shown in table II. Techniques like Mindfulness Meditation, which focuses awareness on the present moment, and Progressive Muscle Relaxation, involving the progressive tensing and releasing of muscle groups, have been shown to effectively reduce stress [21]. Diaphragmatic Breathing, characterized by deep, slow breaths from the diaphragm, activates the parasympathetic nervous system, promoting relaxation [22]. Cognitive Behavioral Therapy (CBT) helps in identifying and modifying negative thought patterns, a significant factor in stress management [23]. Physical practices such as Yoga and Pilates combine movement with breathwork and mindfulness, offering a holistic approach to stress reduction [24]. Spending time in nature and engaging in regular exercise have also been associated with improved mood and stress relief [25]. The importance of social connection and gratitude practice, focusing on positive experiences, is increasingly recognized for its role in emotional well-being [24]. Acceptance and Commitment Therapy (ACT) encourages accepting difficult thoughts and focusing on meaningful life aspects [26]. Additionally, Brainwave Meditation and Heart Rate Variability (HRV) Training, which involves training specific brainwave patterns and guided breathing exercises to improve HRV respectively, are emerging as effective techniques [27]. A Score, a personalized daily metric calculated based on sleep, stress, and HRV metrics, motivates the application of these stress management strategies for engineering students, optimizing their well-being. These diverse practices offer students an array of tools to manage stress, each with its unique method and purpose, contributing to a comprehensive approach to mental health and wellness.

In the context of rPPG for stress management, the role of Large Language Models (LLMs) like GPT-4 in AI is multifaceted and vital. LLMs can analyze large rPPG data, interpret inter-beat interval (IBI) data, compute heart rate variability (HRV) metrics, and provide personalized reports to users [28]. Moreover, they can suggest suitable

	Practice	Description
1	Mindfulness Meditation	Present moment awareness
2	Progressive Muscle Relaxation	Tension-release of muscle groups
3	Diaphragmatic Breathing	Deep, slow breaths from diaphragm
4	Cognitive Behavioral Therapy (CBT)	Identifying and modifying negative thought patterns
5	Yoga and Pilates	Movement, breathwork, mindfulness
6	Spending Time in Nature	Nature exposure for improved mood
7	Regular Exercise	Physical activity for stress relief
8	Social Connection	Importance of relationships in well-being
9	Gratitude Practice	Focusing on positive experiences
10	Acceptance and Commitment Therapy (ACT)	Acceptance of difficult thoughts and values
11	Brainwave Meditation	Training specific brainwave patterns

TABLE II: Wearables Recommended Practices

stress management practices and optimal times for these practices, tailored to individual needs [29]. Once the HRV metrics are computed, LLMs can generate personalized reports. LLMs can recommend practices such as mindfulness meditation, yoga, or specific breathing exercises [29]. They can also suggest the most effective times for these practices, considering the user’s schedule and stress patterns. It offers a data-driven, customized approach to managing stress, allowing engineering students to optimize their well-being and academic performance.

Our contribution is as follows:

- Developed a methodology for minimal-resource rPPG signal calculation from facial video frames.
- Experimented with 14 participants and 42 videos from an rPPG dataset to test the methodology’s consistency and reliability in cardiovascular signal extraction.
- Utilized advanced signal processing, including FastICA [30], for PPG signal analysis from video frames, and validated the results against standard Blood Volume Pulse (BVP) data.
- Implemented a vector database of research papers on stress management for LLM context and background knowledge.
- Implemented a Retrieval Augmented Generation (RAG) vector database of over 50 research papers using the ClarifAI RAG model [31] for enhanced LLM context and background knowledge.

RELATED WORKS

Recent studies have highlighted the multifaceted nature of stress among engineering students. Armstrong et al. (2022) found that distressed engineering students are significantly less likely to seek professional help for mental health concerns compared to their non-engineering peers [32]. Furthermore, a study conducted by Lilley and Larnell (2023) on historically minoritized graduate students in STEM, including engineering, identified the impact of continuous microaggressions and social isolation on their mental health. This research highlighted the need for evidence-based support systems specifically designed for students from historically marginalized communities to mitigate the effects of intimidating academic environments [33]. Another study, focusing on the Indian context, highlighted the role of interpersonal stressors, including changes in social activities and disagreements with peers, as significant contributors to students’ stress. The study also pointed to financial concerns and family responsibilities as key factors affecting students’ mental well-being, with many students juggling multiple responsibilities alongside their academic pursuits ([34]).

Development of rPPG Technology

In the development of rPPG technologies, significant challenges arise in real-time data acquisition and processing, particularly when integrating with systems like LLMs. One of the key challenges has been adapting rPPG algorithms to work effectively across diverse demographics and in various environmental conditions, as traditional connected PPG algorithms often focus on homogenous subject groups in stationary laboratory settings. Recent advancements in rPPG have enhanced its accuracy and adaptability, particularly in varied environmental conditions beyond

the confines of a laboratory ([35]). There is further development of algorithms capable of handling nonuniform illumination changes and subject motion such as the chrominance-based remote PPG algorithm (CHROM) and the Spatial Subspace Rotation (SSR) algorithms that demonstrate enhanced performance in extracting the pulse signal, even under varying skin tones and lighting conditions [36]. These improvements address earlier challenges in rPPG, such as demographic homogeneity and stationary settings, as highlighted in studies exploring biases in rPPG methods [37]. Furthermore, the clinical efficacy of rPPG in measuring vital signs like respiratory rate has been validated in real-life settings, as demonstrated in hospital-based trials ([38]). The SerenePulse webapp harnesses a webcam or selfie camera to capture heartbeats by analyzing fluctuations in light intensity reflected from the skin, a fundamental principle of rPPG technology.

HRV metrics

In this research, we build upon previous research [16] that detailed on HRV metrics and stress analysis. Heart rate variability (HRV), calculated from the input of rPPG, inter-beat intervals is a crucial physiological marker that offers insights into the autonomic nervous system's (ANS) functioning [16]. It reflects the dynamic interplay between the sympathetic and parasympathetic branches of the ANS, highlighting the body's adaptability to stress and relaxation states [39]. Among HRV metrics, SDNN is indicative of autonomic flexibility and cardiac health ([4]). In contrast, RMSSD, focusing on short-term variations in HRV, is particularly sensitive to the influence of the parasympathetic nervous system, making it a vital measure for assessing rapid heart rate changes due to stress and relaxation ([4]). Additionally, frequency-domain measures like the LF/HF ratio and Heart Coherence(HC) provide further insights into autonomic balance, with higher ratios indicating sympathetic dominance and lower ones suggesting parasympathetic dominance [39]. Even more, the Baevsky Stress Index (BSI) is a composite measure derived from HRV that provides an estimate of stress levels, incorporating variability and the predominant rhythm of the heart rate ([4]). For a detailed view of these metrics, please refer to the table in the figure III.

HRV Metric	Domain	Significance
SDNN	Time	Autonomic flexibility and cardiac health.
RMSSD	Time	Assess rapid heart rate changes due to stress.
BSI	Time	Assess stress levels
HC	Time	Rhythm Harmony
LF	Frequency	Autonomic balance and stress response.
HF	Frequency	Parasympathetic dominance and relaxation.
LF/HF Ratio	Frequency	Sympathetic / parasympathetic dominance

TABLE III: HRV metrics

Integration of Large Language Models (LLMs)

The integration of LLMs like OpenAI's GPT-4 into healthcare technology, particularly for analyzing complex physiological data such as heart rate variability (HRV) metrics, marks a significant advancement [40]. It is growing at a fast rate due to their ease of use, low cost, widespread availability, extraordinary projected growth, and notably swift fine-tuning capability for specific tasks or domains [41]. The implementation of innovative techniques such as Self-Questioning Prompting has notably improved LLMs' performance in clinical tasks, facilitating a more accurate analysis of HRV data for psychological state assessments [42]. GatorTronGPT, a clinical LLM developed by pre-training the GPT-3 architecture, exemplifies this advancement to excel in complex tasks in contextual responses [43]. LLMs offer substantial support in areas such as clinical decision-making, efficient data processing, summarizing research data, and patient interaction [44]. This highlights the potential of LLMs like GPT-4 in healthcare applications. According to Rahaman et al., GPT-4 by OpenAI demonstrates significant improvements over its predecessor, GPT-3.5, in areas such as training data optimization, computation speed, answer quality and overall performance. It excels in translating languages, answering complex questions, and interpreting human emotions, making it an unparalleled choice for integrating with HRV metrics for health monitoring [45]. Another study indicates that ChatGPT-4 outperforms ChatGPT-3.5 and BARD by Google Inc. in several reasoning tasks, particularly in abductive reasoning, mathematical reasoning, and commonsense reasoning [46]. Therefore, in this study, we chose GPT-4 as our preferred LLM model.

Educational Implications in Engineering

Easy access to psychological monitoring and measurement is imperative in engineering education due to the unique stressors associated with this field. Studies have shown that the engineering culture, often perceived as masculine, competitive, and exclusionary, can lead to significant stress and mental health challenges for students, particularly for women and students of color [47]. This environment is characterized by a belief in enduring rigorous academic demands as a path to success. It creates a culture where stress and poor mental health are normalized and students may view high stress as an inherent and necessary part of their education [47]. The SerenePulse project addresses these issues by providing real-time emotional and physiological monitoring enabling students to regulate stress levels without additional gadgets.

METHODOLOGY

Our methodology for extracting (Inter Beat Intervals) IBI from rPPG signals from a webcam employs a multi-stage process designed for accuracy and efficiency as shown in our GitHub ¹. Our data flow as shown in figure 1 can be itemized as the following:

- Advanced video frame processing for precise ROI (Region of Interest) extraction, crucial for accurate rPPG signal derivation.
- Utilization of detrending methods to remove baseline drift, improving the fidelity of extracted cardiovascular signals.
- Spatial averaging across facial regions of interest and calculating Green/Red + Green/Blue (GRGB) ratios to emphasize the blood volume pulse signal, alongside robust normalization for signal consistency.
- Implementation of normalization, FastICA, and Fourier Transform for signal clarity and component separation, enhancing signal-to-noise ratio in GRGB time series.
- Application of second-order filtering techniques to clean the signal and identify IBI data from peaks, facilitating heart metric analysis.
- Integration of statistical analysis to validate the methodology, ensuring reliability and accuracy of the rPPG signal extraction and analysis process.

Preprocessing

In the pre-processing stage of our rPPG signal extraction methodology leverages spatial averaging across specific facial regions of interest—forehead, left cheek, and right cheek—identified using the MediaPipe Face Mesh algorithm. This step is crucial for reducing noise and enhancing the quality of the captured signals due to the consistent blood flow and minimal motion artifacts present in these areas, as well as their favorable skin tone characteristics for light penetration [48], [49]. Thereafter, to enhance the rPPG signal extraction from the RGB signal, our methodology employs a Butterworth bandpass filter, optimizing the signal by detrending and filtering across predetermined time windows. The signal is processed through six 10-second, non-overlapping windows using a sixth-order Butterworth bandpass filter with a frequency range of 0.65 to 4 Hz, streamlining the signal preparation without additional optimization steps [50].

Among RGB color channels—Red (R), Green (G), and Blue (B), the green channel plays a pivotal role due to its close similarity to the PPG signal. This is because hemoglobin that carries oxygen-transporting protein in the blood reaches its maximum level of absorption in green light [18]. As the light intensity fluctuations affect all channels equally, the ratio of the green-to-red (GR) and green-to-blue (GB) channels is applied here. Thereafter, z-score standardization is conducted by subtracting the mean and dividing by the standard deviation, tailored to each signal's dimensionality to optimize the signal. It is proven that the sum of these ratios (GR + GB) improves the

¹https://github.com/datasci888/ASEE_June_2024

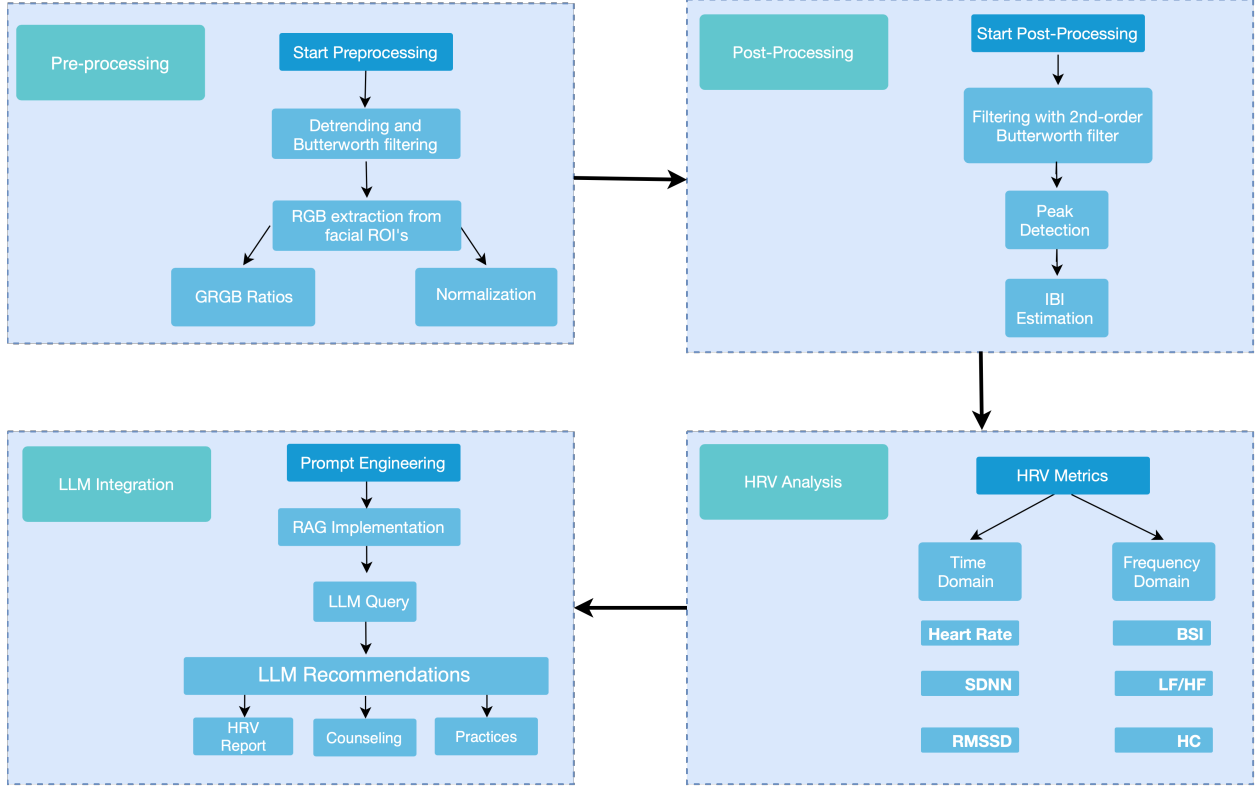


Fig. 1: HRV Analysis Pipeline

quality of the extracted rPPG signals when compared to other conventional methods [51]. Therefore, we continued to process the GRGB signal as below.

After the above process, the Fourier Transform is applied to the time-domain rPPG signal, converting it into the frequency domain to unveil the spectral components. This transformation allows for the precise analysis of dominant frequencies that are indicative of vital physiological signals [51].

$$F(\omega) = \int_{-\infty}^{\infty} f(t)e^{-j\omega t} dt$$

Subsequently, a second-order bandpass filter between 0.65 Hz and 3.5 Hz for heart rate, corresponding to 39 BPM and 210 BPM—is employed to isolate these significant frequency components while excluding others. Vital signs are extracted by pinpointing the peak frequency within the filtered spectrum, with HR determined by multiplying this frequency by 60 to convert it to beats per minute (BPM) [52].

HRV Metrics

Continuing from the detailed methodology for HRV analysis, we focus on translating IBI data into actionable heart metrics that provide comprehensive insights into an individual's cardiovascular and autonomic nervous system function. By employing both time-domain and frequency-domain analyses, we leverage the rich information contained within the IBI data to compute key HRV metrics. This dual-faceted approach allows for a holistic assessment of heart rate variability, capturing both the overall variability and the specific autonomic influences on heart rate dynamics. The time-domain analysis yields metrics such as SDNN and RMSSD, reflecting overall HRV and parasympathetic

activity, respectively. Meanwhile, the frequency-domain analysis, through spectral decomposition of the IBI series, provides insights into the sympathetic and parasympathetic balance via LF, HF components, and their ratio. This comprehensive analysis framework not only enhances our understanding of autonomic nervous system modulation of heart rate but also facilitates the identification of physiological responses to stress and relaxation, as well as autonomic balance, through metrics like the BSI. HC is a measure of the harmony and synchronization between the heart's rhythmic patterns, breathing, and blood pressure oscillations, reflecting the efficiency and balance of the autonomic nervous system. Lower levels of HC are often associated with elevated stress, whereas higher coherence levels indicate a relaxed, stress-resilient state. It represents a physiological state where the body's systems operate with high coordination and efficiency, leading to increased emotional stability and resilience to stress. The integration of these diverse HRV measures offers a robust tool for monitoring cardiac health, stress levels, and autonomic function [16].

HRV Metric	Formula
Heart Rate	$\text{Pulse}(\{IBI_i\}) = \frac{60}{\frac{1}{N} \sum_{i=1}^N IBI_i}$
SDNN	$\text{SDNN}(\{IBI_i\}) = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (IBI_i - \overline{IBI})^2}$
RMSSD	$\text{RMSSD}(\{IBI_i\}) = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} (IBI_{i+1} - IBI_i)^2}$
LF/HF Ratio	$\text{LF/HF Ratio} = \frac{\text{LF Power}}{\text{HF Power}}$
Baevsky Stress Index (BSI)	$\text{SI}(\{IBI_i\}) = \frac{\text{amp}(\text{mod}_{50ms}(\{IBI_i\}))}{2 \times \text{mod}_{50ms}(\{IBI_i\}) \times 3.92 \times \text{SDNN}(\{IBI_i\})}$
Heart Coherence	$\text{Heart Coherence} = \int_{f_0-0.015 \text{ Hz}}^{f_0+0.015 \text{ Hz}} \text{Power Spectrum}(f) df$

TABLE IV: HRV Metrics and Their Formulas

Validation

The methodology for validating rPPG-derived IBI calculations involves a comparative analysis with reference IBI obtained from the UBFC-PHYS dataset's BVP measurements. This process includes loading BVP data, typically in standard formats, and calculating reference IBI through peak detection algorithms to identify heartbeats. The reference IBI is then compared to rPPG-derived IBI using statistical measures such as MAE, RMSE, and Pearson's correlation to assess accuracy. These statistical measures serve as quantitative metrics that allow for a precise evaluation of the degree of agreement between rPPG-derived IBI and reference IBI.

LLM Integration

Integrating HRV metrics with OpenAI's LLM involves a sophisticated process where the LLM plays a critical role in analyzing the complex data from HRV metrics to generate comprehensive reports and personalized recommendations. This process leverages the LLM's advanced natural language processing capabilities to interpret and provide insights into the physiological data, something traditional algorithms cannot achieve with the same level of nuance and understanding. The choice of OpenAI's LLM, particularly for its ability to handle diverse datasets and generate coherent, insightful analyses, underlines its unmatched capability in extracting meaningful conclusions from complex patterns in HRV data. OpenAI's GPT-4 is selected over other LLMs due to its superior performance in understanding and generating human-like text across a wide range of tasks and domains [45]. This integration enables a dynamic feedback loop where HRV metrics inform the LLM's analysis, which in return offers tailored health and wellness advice, demonstrating a powerful application of AI in personal health monitoring.

RESULTS

This study embarked on an exploration of a novel methodology for extracting and analyzing PPG signals from video frames, leveraging facial regions of interest (ROIs) such as the forehead, left cheek, and right cheek. To ensure

consistency across analyses, the first 1000 frames were extracted from each video segment. These frames underwent a series of preprocessing steps, including the application of a facial mesh to highlight ROIs and the extraction of mean pixel values from these areas. Subsequently, the extracted signals were subjected to Butterworth bandpass filtering to isolate relevant frequency components, followed by detrending to remove baseline drift, thus enhancing signal clarity. The study utilized advanced signal processing techniques, including Fast Independent Component Analysis (FastICA), to separate mixed signals into their independent components. By comparing the results with standard Blood Volume Pulse (BVP) data, we aimed to validate the accuracy and reliability of our approach in extracting meaningful cardiovascular signals from facial video data.

In the initial step, we processed the extracted video frames to identify and highlight regions of interest (ROIs) on the human face using MediaPipe's FaceMesh technology [53]. This process involved the application of a facial mesh to each frame, which facilitated the precise detection and delineation of facial landmarks [54]. For each frame processed, we specifically targeted three critical ROIs known for their relevance in PPG signal extraction: the forehead, left cheek, and right cheek, as they were proven for optimal accuracy [55]. In the subsequent signal-processing step, each ROI was visually highlighted with distinct colors for clear differentiation as shown in figure 2.

Processed Frame with Face Mesh and Highlighted ROIs

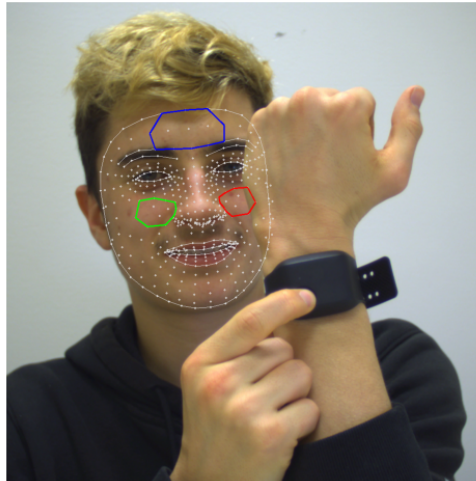


Fig. 2: Highlighted Regions of Interest

The application of Butterworth bandpass filtering is then applied to isolate the relevant frequency components inherent to mitigate the influence of various artifacts such as noise, lighting variations, and camera noise, which can obscure the rPPG signals. The Butterworth filter, with a linear phase characteristic, ensures relative timing relationships between different frequency components of the signal are maintained [56]. The filtered signals in (figure 3) suggest that the filter has successfully extracted the underlying trends that are common across all three channels.

Non-stationary trends in the signal such as simple drifts or more complex variations in the HRV signal can distort both time and frequency domain analyses. To reduce this kind of pattern shifts in the data over time, we then applied the detrending method on the filtered signals to eliminate slow-varying trends caused by factors like face motion or respiration-induced baseline drift [57]. As we can see in figure 4, there was no visible head movement in the analyzed time frame, and therefore, the curves remain almost the same to human eyes as in filtered signal.

Research has shown that the green light channel has higher sensitivity to blood volume changes beneath the skin, a property that makes it exceptionally suited for detecting the subtle variations associated with cardiac cycles [18]. Even more, we calculated the ratios of green-to-red (GR) and green-to-blue (GB) channels for each identified facial ROI, including the forehead, left cheek, and right cheek. Then we calculated the GRGB ratio (GR+GB), as it significantly improves the accuracy of heart rate estimation from video-derived rPPG signals [51].

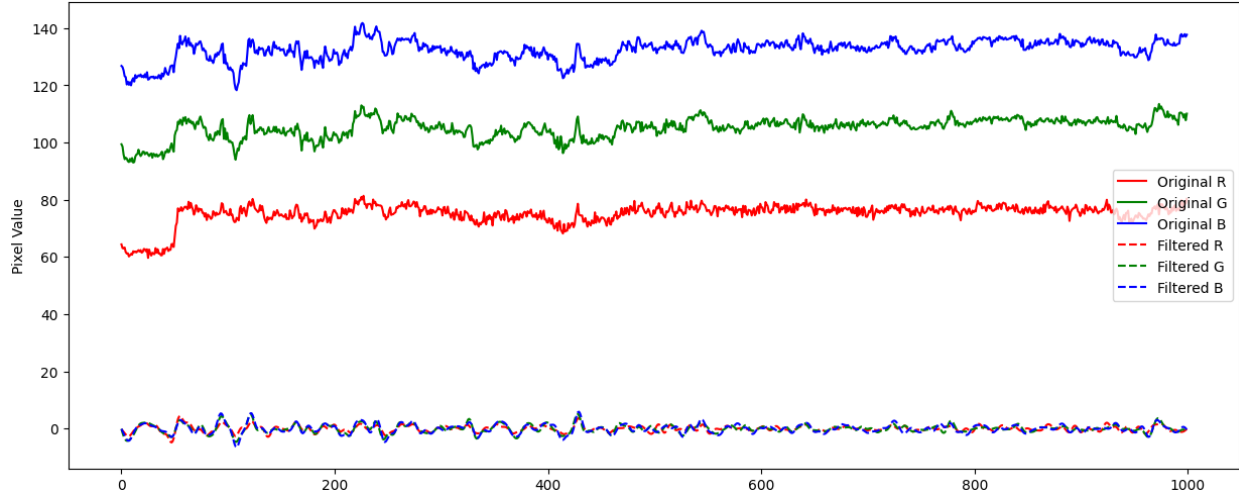


Fig. 3: Forehead Signal After Filtering

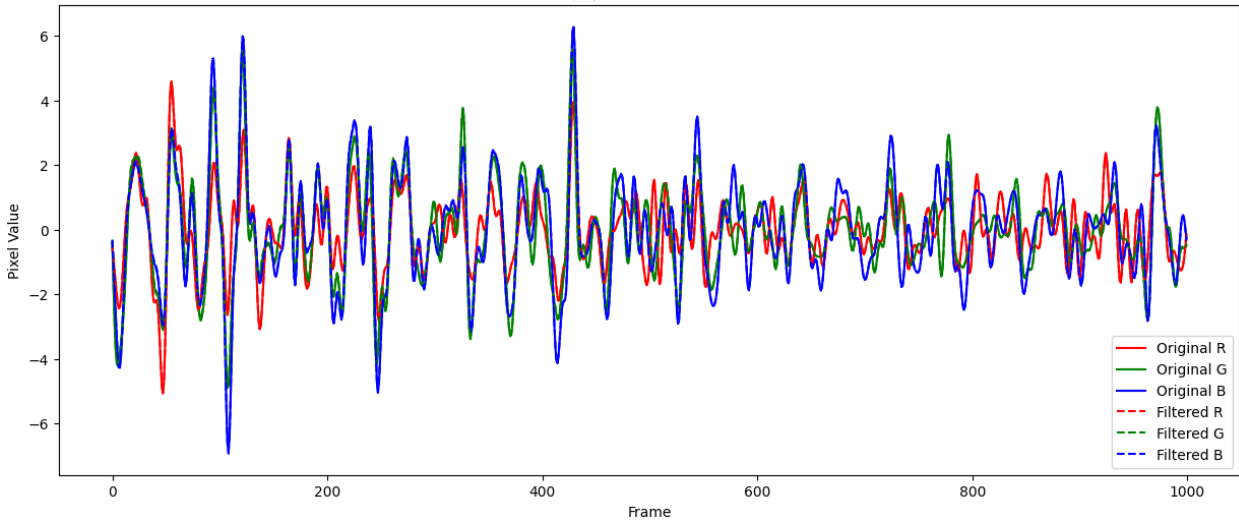


Fig. 4: Forehead Signal After Filtering

Normalization mitigates the impact of outliers and scales the data to a uniform range, thereby facilitating more reliable comparisons and analyses. Two distinct normalization techniques were employed — Winsorizing and z-score normalization. Winsorizing effectively reduces the influence of outliers that could skew the analysis by limiting the extreme values in the distribution. Subsequently, z-score normalization was applied to standardize the data to have a mean of 0 and a standard deviation of 1 which enables more accurate identification of variations in the GRGB signals. Thereafter, this normalized data (Figure 6) is passed into the function of Independent Component Analysis (ICA).

ICA is implemented to separate the mixed signals into their constituent components that are the most representative of the cardiovascular pulse wave. As mentioned in the study by Lewandowska et al., the second component was identified as being the most representative of the heart pulse [58]. This was verified in our experiment which improved the accuracy of heart rate calculation by 2.8%. ICA splits the signal based on their statistical properties (figure 6) that represent underlying sources that contribute to the observed signal variations, which may include the physiological pulse signal and other noise factors. From these components, through experimentation, the second component that represents a periodic pattern that corresponds to the cardiac cycle is selected for the Fourier Transform.

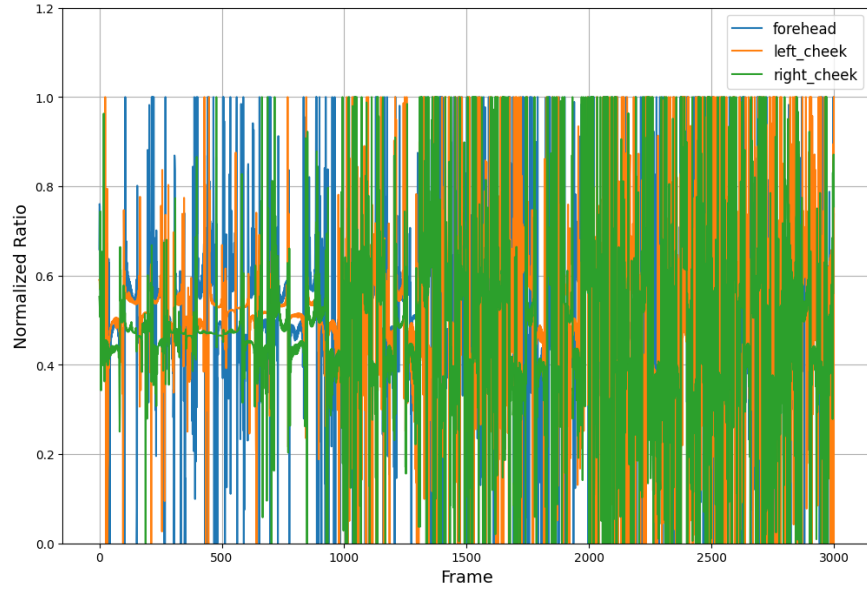


Fig. 5: Normalized Color Channel Ratios Over Time

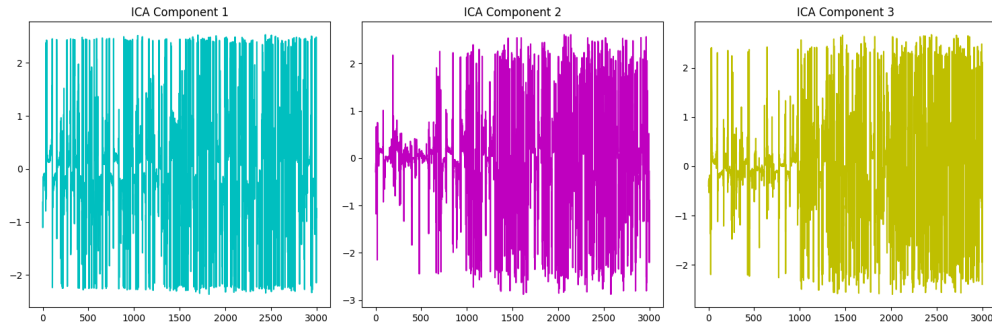


Fig. 6: ICA components

Fourier transformation facilitates the identification of dominant frequency components within the physiological heart rate range, thereby improving the precision of peak detection and heart rate estimation [59]. After enhancing the signal-to-noise ratio for vital signs extraction as seen in figure 7, a 2nd order bandpass filter (0.75 Hz to 4.5 Hz) is applied that further refines the signal by isolating frequencies that represent the normal heart rate range of 45 to 270 bpm [60]. The effect of 2nd order bandpass filter can be observed in the figure 8.

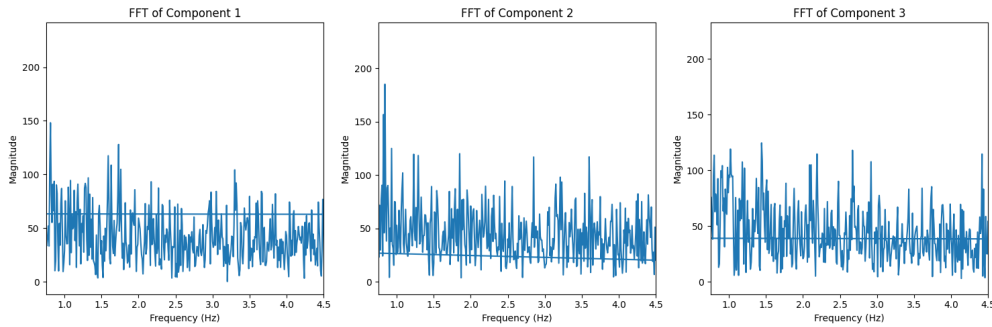


Fig. 7: Fourier Transform of ICA components

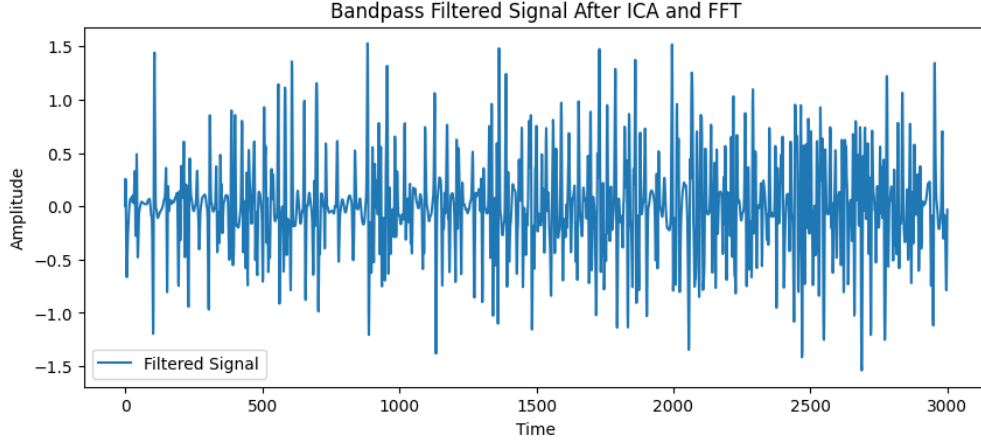


Fig. 8: Bandpass Filtered Signal After ICA and FFT

Bandpass Filtered Signal After ICA and FFT helps to compute the pulse spectrum for computing the Heart Rate through peak detection. The process of peak detection involves identifying local maxima in the time-domain signal that corresponds to the systolic phase of the cardiac cycle. The heart's contraction results in a peak in blood volume that causes a peak in the PPG signal as well [61] as seen in 9. IBIs are then calculated by measuring the time between consecutive peaks and the average heart rate is computed from these IBIs.

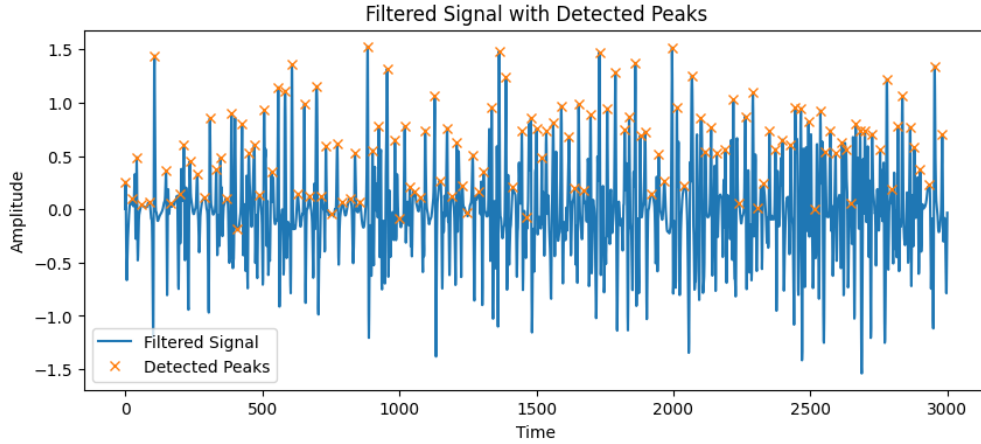


Fig. 9: Filtered Signal with Detected Peaks

The calculation of IBIs from the time elapsed between consecutive peaks, and the subsequent computation of the average heart rate, yielded a heart rate of 77.16 beats per minute (bpm) for a selected video. Furthermore, we found the HRV metrics as SDNN, RMSSD, BSI, and LF/HF Ratio were calculated as 0.214901, 0.293350, 1.066506, and 0.605642, respectively, as shown in the table V for the same individual.

The UBFC-PHYS dataset encompasses data obtained from biometric sensors, notably the Empatica E4 wristband, acclaimed for its precision in recording physiological signals such as blood volume pulse (BVP) and electrodermal activity (EDA). The HRV metrics for 14 out of 56 participants's videos were calculated for the given time frame to measure the effects of the pipeline. To validate these values, the statistical tests were applied to the HRV metrics—SDNN, RMSSD, BSI, and LF/HF Ratio and were compared with the values found from the ground truth BVP datasets (Table VI).

The results revealed high correlation coefficients for all metrics, indicating a robust linear relationship between the current calculations and the BVP dataset in metrics like HR, SDNN, RMSSD, and BSI. In statistical analysis,

	Metric	Current Calculation	BVP Dataset Calculation
0	Heart Rate	77.160080	74.373089
1	SDNN	0.214901	0.191179
2	RMSSD	0.293350	0.259268
3	BSI	1.066506	1.404592
4	LF/HF Ratio	0.605642	0.514026

TABLE V: HRV metrics Comparison - Individual

Metric	MAE	RMSE	Correlation
Heart Rate	6.07	6.436	0.926
SDNN	0.014	0.016	0.966
RMSSD	0.013	0.014	0.988
BSI	0.192	0.241	0.989
LF/HF Ratio	0.217	0.296	0.998

TABLE VI: Statistical Analysis - 14 participants

MAE and RMSE assess the differences between values predicted by a model or an estimator and alternatively measured actual values. In the validation process, the MAE and RMSE values provide insight into the average magnitude and the square root of the average squared differences of the errors, respectively, with lower values indicating higher accuracy. The results suggest that the current calculations are relatively accurate, with especially strong accuracy in metrics like HR, RMSSD, SDNN, and BSI, based on their lower MAE and RMSE values and high correlation with the gold standard BVP measurements. Furthermore, by computing the relative error for each metric the mean accuracy across different HRV metrics, including Heart Rate, SDNN, RMSSD, BSI, and LF/HF Ratio, was then aggregated, revealing an average accuracy of 0.9211.

DISCUSSION

HR serves as a fundamental metric, offering insights into beats per minute which reflect overall cardiovascular health and activity levels. SDNN, representing the overall variation in heartbeat intervals, sheds light on the balance between sympathetic and parasympathetic nervous system activities, encapsulating the body's adaptive responses to environmental and psychological stressors. RMSSD, focusing on short-term variations in heart rate, predominantly assesses the parasympathetic nervous system's function, offering an indicator of stress response and vagal tone. BSI, derived from BVP signals, quantifies the signal-to-noise ratio of brain activity, providing a measure of the brain signal's clarity and integrity. Lastly, the LF/HF Ratio elucidates the balance between sympathetic and parasympathetic influences within the HRV spectrum, serving as a critical indicator of autonomic nervous system predominance. SDNN measures the dispersion or spread of the NN (normal-to-normal) intervals, which are the time intervals between consecutive heartbeats that are associated with the sinus node activity. Overall, the model achieved high accuracy across various metrics, including SDNN, RMSSD, BSI, and LF/HF ratio but needs more research to improve its accuracy (Table VII).

In our model, we went further and integrated heart rate variability (HRV) metrics with an OpenAI language model for health insights, the methodological approach encompasses a seamless fusion of advanced data analysis and natural language processing capabilities. The integration employs a sophisticated pipeline involving the submission of HRV data, alongside a detailed prompt that contextualizes the data within the realms of stress management, sleep irregularities, and potential health interventions. By channeling HRV data through the language model, we enable

the extraction of nuanced health insights, leveraging the LLM’s capacity to interpret complex datasets and provide actionable recommendations. Based on the prompt engineering, the recommendations span a broad spectrum, from mindfulness practices and physical activities to sleep hygiene and diet adjustments, all tailored to the individual’s specific health indicators derived from the HRV analysis as seen in the Appendix. The resultant insights underscore the model’s adeptness in translating quantitative data into qualitative advice, facilitating a holistic approach to health optimization.

Metric	Health Insight
BSI	Signal-to-noise ratio of brain activity, higher indicates stronger brain signal.
Heart Rate	Average number of heartbeats per minute, reflects cardiovascular health and activity.
LF/HF Ratio	Balance between sympathetic and parasympathetic nervous system activity, higher LF suggests more stress/excitation.
RMSSD	Short-term heart rate variability, reflects parasympathetic nervous system function.
SDNN	Overall heart rate variability, reflects both sympathetic and parasympathetic activity.

TABLE VII: HRV Health Insights

Even more, the retrieval Augmented Generation (RAG) approach implemented in this study, aims to enhance mental health monitoring by providing live, personalized feedback ². Clarifai provides a complete platform for building and deploying RAG systems, including data preprocessing, model training, and API integration [31]. This experiment involved creating and querying a vector store of over 50 research papers on psychological stress management optimized for textual similarity searches. This helps in developing the right context and background knowledge before querying the LLM for insight generation without hallucinations.

The methodology outlined for integrating HRV metrics with OpenAI’s language model for health insights provides a foundation for developing an rPPG app, either as a web or mobile application. Leveraging the extensive reach of smartphones, with nearly 6.5 billion users globally [62], this approach offers a unique opportunity to deliver personalized health and wellness insights on a massive scale. By utilizing such a pipeline, developers can harness the power of AI to interpret complex health data, offering users actionable guidance toward improving their mental and physical well-being. This strategy aligns with the current technological and health trends, highlighting the potential for widespread adoption and impact.

CONCLUSION

We often manage physiological levels like blood sugar and cholesterol diligently, recognizing their importance. However, mental health monitoring, despite its significance proven for disease prevention, frequently lacks real-time attention and intervention. This study introduces a methodology for developing a smartphone app integrated with an LLM for live feedback, offering a low-cost, ubiquitous stress management system. This innovation, providing almost immediate AI psychological support, lays the groundwork for future bio-feedback advancements, emphasizing the crucial role of mental health in our overall well-being.

LIMITATIONS OF THE STUDY

While the study’s approach offers innovative methods to analyze and provide health recommendations based on HRV data, it was limited to a small number of participants within a selected dataset. Incorporating additional

²https://github.com/datasci888/ASEE_June_2024

methodologies, especially the application of neural networks, holds promise for improving accuracy, particularly when dealing with larger datasets. Further expansion in demographics, such as including participants from diverse age groups, skin colors, and geographical locations, could provide a more comprehensive understanding of the model's effectiveness across various populations.

FUTURE DIRECTION

Moving ahead, we would deploy the developed methodology into a web app or a mobile app to integrate advanced stress analysis and intelligent stress management with seamless hardware integration. Even more, real-time feedback through rPPG technology would be introduced and compatibility with wearable devices like Apple Watch, Fitbit, and Whoop via API access would enhance its utility. This wireless approach could revolutionize how individuals manage their mental health, productivity, and well-being in a connected world, at a low cost.

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APPENDIX

Query to the LLM

Given the user’s heart rate variability (HRV) metrics showing signs of stress and potential sleep irregularities, provide a detailed analysis and suggest practices to improve their mental and physical health. Consider the following categories and practices:

- Mindfulness: Guided meditation, Breathwork exercises, Pranayama
- Physical Activity: Regular exercise, Yoga, Dance, Hiking
- Sleep Hygiene: Consistent sleep schedule, Relaxing bedtime routine
- Relaxation Techniques: Progressive muscle relaxation, Deep breathing exercises
- Social Connection: Spending time with loved ones
- Time Management: Creating a schedule and setting realistic goals
- Healthy Diet: Limiting processed foods and sugary drinks

Incorporate breathing practices, yoga, and other relevant activities to offer a holistic approach to well-being.

Metric	Calculation	Timestamp
Heart Rate	79.93322	7:12:32
SDNN	0.198726	7:12:32
RMSSD	0.281695	7:12:32
BSI	1.206472	7:12:32
LF/HF Ratio	0.631975	7:12:32

TABLE VIII: HRV metrics of a user

Open AI Assistants GPT-4 response:

Analyzing the provided heart rate variability (HRV) metrics can give us insight into the autonomic nervous system (ANS) functioning and an individual’s stress response. These HRV metrics suggest signs of stress and potential sleep irregularities, which could impact both mental and physical health. Here’s a breakdown of the key HRV metrics provided:

- Heart Rate (HR): The average beats per minute. An HR of 79.933 may be normal or slightly elevated depending on the individual’s age, fitness level, and circumstances surrounding the measurement.
- SDNN (Standard Deviation of NN intervals): Reflects the overall heart rate variability. The SDNN of 0.198726 is relatively low, indicating reduced HRV. Generally, higher HRV is linked to better cardiovascular fitness and stress resilience.
- RMSSD (Root Mean Square of the Successive Differences): Primarily reflects the parasympathetic nervous system activity, relating to relaxation and recovery. An RMSSD of 0.281695 is low, suggesting potential stress or lack of recovery.
- BSI (Biomarker Stress Index): An index to evaluate stress levels. A BSI of 1.206472 could indicate elevated stress.

- **LF/HF (Low Frequency/High Frequency) Ratio:** Reflects the balance between sympathetic (stress response) and parasympathetic (relaxation response) activity. A lower ratio, like 0.631975, often indicates a parasympathetic dominance or relaxation state, which could be misleading without other contextual information or considering it alongside other low HRV metrics.

Given these insights, let's explore tailored practices in each category that can help improve mental and physical health: article

1. Mindfulness:

- **Guided Meditation:** Start with 5-10 minutes daily, using apps or online videos.
- **Breathwork Exercises:** Practice slow, deep breathing techniques (like the 4-7-8 technique) to activate the parasympathetic nervous system.
- **Pranayama:** Incorporate yogic breathing exercises such as Nadi Shodhana (alternate nostril breathing) to balance and calm the mind.

2. Physical Activity:

- **Regular Exercise:** Aim for at least 30 minutes of moderate activity most days. This can include walking, swimming, or cycling.
- **Yoga:** Engage in yoga practices that emphasize relaxation and flexibility, such as Hatha or Yin yoga, to reduce stress and improve HRV.
- **Dance, Hiking:** Fun and engaging activities like dance or hiking outdoors can improve your mood and reduce stress.

3. Sleep Hygiene:

- **Consistent Sleep Schedule:** Go to bed and wake up at the same time every day, even on weekends.
- **Relaxing Bedtime Routine:** Incorporate activities like reading, listening to soft music, or taking a warm bath to signal your body it's time to wind down.

4. Relaxation Techniques:

- **Progressive Muscle Relaxation:** This involves tensing each muscle group and then relaxing them to release physical tension.
- **Deep Breathing Exercises:** Practice regularly to improve vagal tone and HRV.

5. Social Connection:

- **Spending Time with Loved Ones:** Schedule regular activities or conversations with friends and family to enhance emotional support and reduce stress.

6. Time Management:

- **Creating a Schedule:** Organize your day and set realistic goals to reduce feelings of being overwhelmed.
- **Setting Realistic Goals:** Break down tasks into manageable steps and prioritize essential activities to lessen anxiety and improve focus.

7. Healthy Diet:

- **Limit Processed Foods and Sugary Drinks:** Opt for whole foods, fruits, vegetables, lean proteins, and healthy fats to support overall well-being.