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Preventing Obstructive Sleep Apnea Using A Bio-Control Feedback Prototype Device

Sean Lennon[1], Srushti Kulkarni[2], Harshith Bandaru[3]

[1]Narayana Kuvempu Bhavan, 3J46+8RQ, H A Farm Post, Rachenahalli, Dasarahalli, Bengaluru, Karnataka 560024, India
[2]Sharnbasweshwar Residential Pre-university College, Parimal Prasad Plot No. 1 Ghabre Layout, Kalaburagi, Karnataka, 585103, India
[3]DPS school, Survey No 74, Khajaguda Village, Chitrapuri Colony Post, Hyderabad, Telangana 500104, India

Abstract
Obstructive sleep apnea (OSA) is a common sleeping disorder that can result in shortness of breath due to the relaxation of upper respiratory tract muscles while the patient is asleep. This leads to low blood oxygen saturation and, hence, apnea. OSA is associated with higher risks of hypertension, coronary artery disease, arrhythmias, cardiac failure, and stroke, affecting 5% of the global human population. Thus, early detection and treatment of OSA are crucial. Nowadays, OSA is diagnosed by analyzing EEG signals. Electroencephalographic (EEG) signals are important for monitoring brain activity; this paper focuses on patients with OSA. Unfavorable spikes in the graph, such as head movements, electrical interferences, or even muscle spasms, may interfere with the general EEG frequencies being targeted. Our research was centered on designing a cost-effective electronic circuitry for this device that would efficiently acquire and process EEG signals. We used various methods to improve the device's functionality and accuracy, including rectifications in noise reduction, signal filtering, and structural correction through ICA decomposition. ++Our system, theoretically, achieved a high accuracy rate of 97.14% using Support Vector Machines.

Keywords: Obstructive Sleep Apnea, EEG, ERP, Support Vector Machines, ICA, Prototype

1. Introduction

OSA is a complex and multifaceted, increasingly common, chronic sleeping disorder with multiple associated symptoms and comorbidities [1]. It's usually prevalent in middle-aged and elderly people. It is characterized by recurrent episodes of upper airway obstruction, leading to sleep fragmentation and the person waking up abruptly in the middle of the night and being in a state of arousal because of the low oxygen saturation in his blood. 936 million adults around the world are estimated to have mild to severe OSA. OSA usually occurs in the REM (rapid eye movement) stage of sleep.

OSA is very tricky to diagnose due to having symptoms that overlap with many other sleeping disorders, and having the disease for a considerably long period can result in cardiovascular diseases and other physiological issues with the body of the patient [2]. OSA does not necessarily have a specific cause, but it can range from multiple conditions or diseases; with the rare case of physicians not being able to find

the root cause of disease as well. Some of the factors that are risk factors for OSA are obesity, age, sex, sedatives, family history, poor lifestyle habits, and upper respiratory tract conditions like enlarged tonsils, nasal congestion, etc. [3]. Some common symptoms of OSA are fatigue, memory loss, depression (due to loss of proper sleep), and daytime somnolence or excessive daytime sleepiness (EDS).

One of the most effective methods is Continuous Positive Airway Pressure (CPAP) therapy, which is a machine that uses mild air pressure to keep breathing through a mask that delivers a constant flow of air to keep the airway open [4]. In this research study, we have established a low-cost platform capable of treating OSA, such as polysomnography, which is considered the gold standard test for the diagnosis of OSA since it records parameters like effort in breathing, air intake, brain waves, oxygen desaturation, etc. [5]. OSA is also diagnosed by analyzing electroencephalogram (EEG) signals. EEG is a non-invasive neuroimaging technique that is widely used in cognitive neuroscience research and clinical neurology [6]. It tends to measure the electrical activity in the brain using electrodes placed on the scalp. Human EEG largely comprises signal power in a range of frequencies from 1 to 30 Hz. In this paper, with the help of a machine learning approach, we were able to create a feedback prototype device that tests several brain-body interactions [7].

2. Discussion

2.1 Obstructive Sleep Apnea: Physiological Mechanisms

People diagnosed with OSA usually have a smaller volume, size, or area of the upper airway. They usually have an increased tongue area and soft palate length, or other conditions such as swollen tonsils, large neck sizes, craniofacial changes, altered muscle function in the upper airway, pharyngeal neuropathy, and fluid shifts to the neck. OSA is related to transient upper airway narrowing, disrupting ventilation. OSA is also more prominent in people with obesity, where they have excessive fat in the neck, which further reduces the volume of the upper airway, which again leads back to OSA. It is also found that OSA usually occurs during REM (Rapid Eye Movement) [8].

2.1.1 Anatomy of the upper airway

OSA is very dependent upon the individual's upper airway anatomy, which explains why some people are more prone to having OSA than others. Usually, when we are all active, our muscles are all active as well and contract and relax, including the muscles on the upper airway, like our palate and tongue, but this changes when we are sleeping because usually when we are sleeping most if not all our muscles relax, including the ones in our upper airway, and this can cause a huge problem because if they relax too much, the soft tissue in the back of the throat collapses and leads to blockage of the airway, which in turn causes breathlessness and is the main process happening in OSA [9]. The relaxation/collapse can be due to a myriad of reasons, and the upper airway has something known as the pharynx, and the collapse of this is what leads to OSA.

The advent of the MRI has helped us gain a deeper understanding of the upper airway, and it's especially helped in the understanding of the growth and development of the upper airway during childhood by showing us an innate scaled 3-dimensional image of the tissues in the upper airway [10].

2.1.2 Pathophysiology of OSA

OSA is characterized by the occurrence of repeated or complete pharyngeal collapses during sleep, which leads to intermittent hypoxia and sleep fragmentation. Usually, the processes and mechanisms behind pharyngeal collapses during sleep are complex and multifactorial, which adds to the difficulty of identifying OSA itself. As mentioned before, several factors influence the stability of the upper airway pharyngeal critical closing pressure (Pcrit), which is a very useful and major determinant of OSA and may be used to help predict the success or failure of CPAP. Apneas and hypopneas occur in the context of anatomical reductions of the upper airway calibre as a result of obesity or maxillofacial or pharyngeal soft tissue abnormalities. The decrease in pharyngeal dilator activity at sleep onset triggers apneas and hypopneas that are ended by microarousals, allowing restoration of muscle activity and upper airway reopening. Other factors, such as pharyngeal neuropathy, impairing protection of upper airway reflexes, or rostral fluid shifting from the legs to the neck during sleep, are potent contributors to pharyngeal collapse [11].

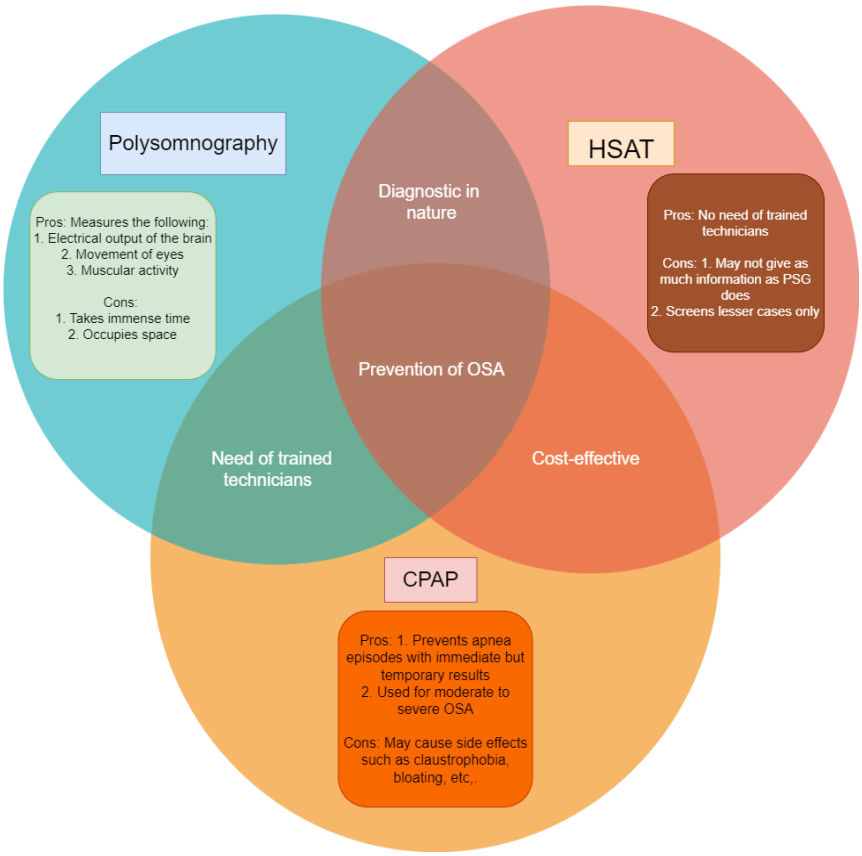
2.2 Bio signals for OSA Detection

OSA has a risk of several complications, such as hypertension and cardiac diseases. The severity of OSA is measured by the number of times it reoccurs every hour. Polysomnography (PSG) records body position, oxygen saturation, and snore signals. Some recent work has shown that oxygen saturation signals provide discriminative information in sparse representation to detect apnea and hypopnea events. According to the American Academy of Sleep Medicine (AASM), OSA can cause hypertension, coronary heart disease, and arrhythmias; in addition to these, it can also cause drowsiness, depression, fatigue, heart stroke, and brain stroke. According to the AASM, the PSG is considered to be the gold standard for OSA detection, which is based on recording the signals the patient experiences overnight and the measurement of many signals via sensors attached to the body. EEGs, EMGs, ECGs, and EOGs monitor the respiratory effort and other physiological signals. After they inspect the data, they use statistical tools to score the OSA events [11]. The traditional visual OSA score is a very tedious and time-consuming process for physicians to conduct, so we have been able to develop alternatives to OSA that are also based on biosignals such as snoring, SpO2, ECG signals, and many others. But all of these involve complex processes like feature extraction, feature selection, etc. [12]. Genio System: Nyxoah's Genio bilateral hypoglossal nerve stimulation system has received FDA breakthrough device designation for treating moderate-to-severe OSA. The system stimulates hypoglossal nerves to trigger muscle contractions and tongue movement, opening the airway during sleep. Obesity and OSA: Obesity is a significant risk factor for OSA. Approximately 70% of OSA patients are obese (BMI $\geq$ 30 kg/m^2). In morbidly obese patients (BMI $\geq$ 40), the prevalence of OSA can be as high as 40–90%.

PSG has many disadvantages, which include the patient having to stay in the hospital for a considerable amount of time and also being very costly. Also, to be able to monitor the patient, we need to attach many electrodes to his body, which makes it very uncomfortable for the person to sleep and may even result in a change in the results. So we need to find new ways to diagnose OSA with as few signals as possible. Urtnasan et al proposed a method for the automated deception of OSA from single-lead ECC using CNN. Hot et al were able to develop an approach for OSA event detection using CNN and single-channel nasal pressure signal and we were able to use CNN to extract ECG features and signals from fully connected neural networks for OSA event detection. [11, 12]. A method by which we can detect

sleep apnea based on how deep the neural network is by using single-lead ECG signals these unlabeled ECG signals have helped us provide useful features obtained by the sparse autoencoder method During the calibration of the sensors at the beginning of the PSG recording, the patients were asked to both speak and snore loudly to differentiate the signals from each other. Thoracoabdominal excursions were recorded via respiratory inductive plethysmography (RIP) on abdominal and thoracic belts [13].

2.3 Conventional Techniques



Treatment for OSA over time has been proven with evidence to improve the patient's outcome and cause disturbance in the sleep pattern two or more times a night. PSG is considered the gold standard test for the diagnosis of OSA since it records parameters like effort in breathing, air intake, brain waves, oxygen desaturation, etc. [14, 15]. So it can provide an idea as well as indications of other sleep disorders, which can be connected to OSA. These results help prevent and treat chronic disorders. In this digital age where machine learning mechanisms help optimize and more efficiently achieve the speed of corporate action and decision-making, it becomes possible to get rapid solutions using algorithms and other tools. OSA and machine learning can help calculate computational analysis, including the efficiency of separate types of therapies for different patients.

Figure 1: Venn diagram comparing the pros and cons of PSG, CPAP, and HSAT for OSA. The chart highlights the unique strengths and limitations of each method, helping to inform decisions regarding the most appropriate diagnostic and treatment approach for individual patients with OSA.

Another notable difficulty that accompanies the diagnosis and treatment of patients with OSA is adequate assessment of biopotential signals during sleep. Historically, polysomnography (PSG) was the common gold standard for evaluating sleep disorders as it is the most comprehensive diagnostic tool that records several physical signals, including the electrical output of the brain, the movements of the eyes, and muscle activity [16]. However, it takes a lot of time and occupies a lot of space, as well as specialized equipment and trained technicians, which increases its overall cost and makes it expensive. Additionally, there is the possibility of patients carrying out Home Sleep Apnea Testing (HSAT) under someone's guidance [17]. However, the biggest limitation of HSAT is its inability to document sleep stages, especially those that alter the apnea-hypopnea index (AHI) value during the sleep study. It may not give as much information as PSG does but it does serve to screen less complicated cases of OSA [18].

CPAP consists of a pump, tubes, and a mask covering the patient's nose or mouth. As air is forced down their throat at positive pressure levels as they sleep, it opens their airway, thus preventing apnea episodes and allowing a person to have a good sleeping cycle. CPAP machines are considered conventional and generally well-accepted treatment options for moderate-to-severe OSA [19]. The Venn diagram given below shows the comparison between the three mentioned treatments for OSA.

2.4 Wearable EEG monitoring system

Wearable EEG systems have recently started to be considered as a means of monitoring Obstructive Sleep Apnea. Such systems provide reliable and non-invasive apnea measurements and sleep patterns [20]. There are several different advantages to using wearable EEG technology instead of conventional PSG: it is flexible, it can be tailored more to customer needs, and therefore one might describe it as another type of home monitor for cases where the illness takes a long time to cure [21].

The weight of wearable monitors is very light, and patients do not feel significantly burdened, to the point where they can tolerate them better than laboratory-based tests like PSG. In other words, a patient can have more natural sleep so that the recorded information may be more healthy and accurate.

It is important to note that these monitors are advantageous for the customer because they can gather more data about sleep patterns and cases of apnea, which stay on most of the time; they can not only track a patient's sleep cycle but also keep a record of its variations and show how severe their OSA has been on different nights. Wearable EEG system data can also provide information to score apneic events in real-time, which means taking more suitable actions for their prescription. Wearable EEG monitors usually comprise multiple electrodes on a headband to detect electrical signals from the brain, which are sent to the embedded code to be tended to [22]. Those algorithms then receive that data, classify the patient's sleep patterns, and identify any interruptions in the schedule that may resemble OSA symptoms such as restricted airflow and oxygen desaturation. Some high-end versions of the wearable EEG system may include other sensors to monitor the heart rate, blood oxygen level, and the effort taken to breathe. They may provide more necessary information than the conventional PSG. Therefore, the question arising here is whether they can be used as a substitute for those that are used in the diagnosis and treatment of OSA.

2.5 Neuroimaging and Machine Learning: Enhancing Understanding of OSA and Cognitive Dysfunction

OSA patients have shown rays of hope with imaging techniques, which have provided strong evidence that connects brain damage and dysfunction with this syndrome. This is a result of several brain-body interactions mentioned earlier. It gives us much insight into other ways that OSA can impact the brain, which is important as the relationship between sleep-related breathing disturbances and cognitive dysfunction is incredibly complex. Neuroimaging studies (specifically EEG) offer a better understanding of brain functions that are and aren't affected by OSA [23].

The machine learning algorithm can also automatically identify different signal patterns and any abnormalities that are related to OSA diagnosis [24]. Several types of applications can be useful in this process of evaluating similar ideas, but machine learning is truly one of the best candidates because of its ability to analyze many various aspects of OSA. The clinical features of OSA and using clinical indices for predicting the outcomes of OSA.

2.5.1 Materials and Components

The Maker UNO development board, accompanied by its essential cable, serves as the backbone for our BioAmp EXG Pill provided via Upside Down Labs. With the BioAmp cable v3 and a tangle of jumper cables, we connect the circuitry, ensuring every component from gel electrodes to the dry 2 Ch electrode-based Brain BioAmp band operates in an ideal fashion. Gel electrodes are a device for transporting the EEG signals transmitted by the dry 2 Ch electrode-based Brain BioAmp band from the patient's prefrontal cortex for analysis. Through the intricate connection of the jumper cables and BioAmp EXG Pill connections, we establish a robust interface between our development board and the electrode-based Brain BioAmp band.

2.5.2 Design and Development

The connections are as follows: VCC to 5V, GND to GND, and OUT to analogue pin A0 on the Maker UNO using jumper cords. The input pin will need to be adjusted in the Arduino script if you are connecting OUT to any other analogue pin. If the power pins (GND & VCC) are switched, your BioAmp EXG Pill will burn up and become unusable (DIE) [25]. The cable end of the BioAmp cable is connected to the JST PH connection on the BioAmp EXG Pill.

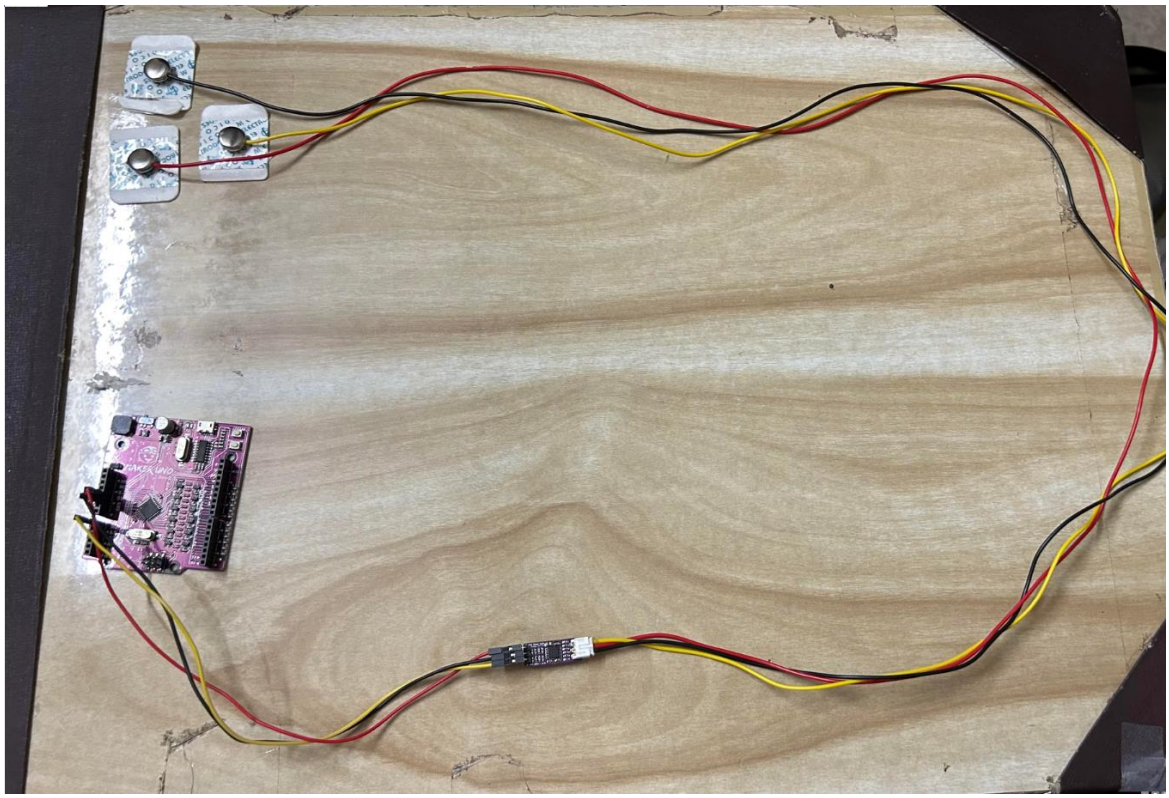
For recording EEG from different parts of the brain, the electrodes have to be placed according to the International 10-20 system for recording EEG [26]. There are two options to measure the EEG signals: either using the gel electrodes or using a dry electrode-based Brain BioAmp Band.

Using gel electrodes to record from the prefrontal cortex part of the brain:

1. The BioAmp cable is connected to the gel electrodes.

2. The IN+ and IN- cables are placed on Fp1 and Fp2 as per the International 10-20 system, & REF (reference) is at the bony part, on the back side of your earlobe.

Using the Brain BioAmp Band to record from the prefrontal cortex part of the



1. Connect the BioAmp cable to the Brain BioAmp Band in a way such that IN+ and IN- are placed on Fp1 and Fp2 as per the International 10-20 system.

2. In this case, the REF (reference) should be connected using a gel electrode.

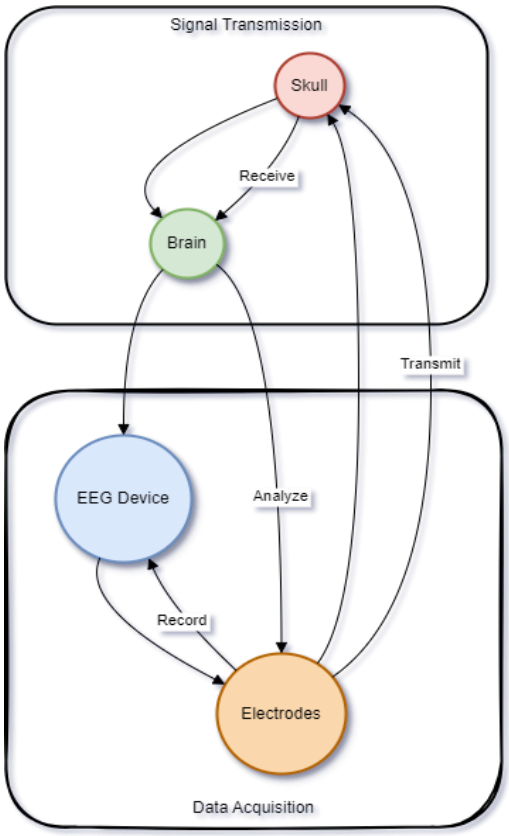
3. Now put a small drop of electrode gel on the dry electrodes (IN+ and IN-) between the skin and the metallic part of the BioAmp cable to get the best results.

The Maker Uno is connected to your laptop using a USB cable (Type A to Type B). In the Arduino app, select the board option 'Arduino UNO' and the COM port to which the Arduino has been connected. We will be using the BackyardBrains Spike Recorder to record and visualize the brain signals [27]. Apply the 50Hz notch filter by clicking the checkbox. You should set the low bandpass filter to 1 Hz and the high bandpass filter to 40 Hz, as we are only recording the EEG signals that range between these frequencies.

Now everything is configured and connected. The signals on the BackyardBrains Spike Recorder screen right now originate from the prefrontal cortex part of your brain and propagate through all the layers to the surface of your skin. To record these EEG signals, you have placed the electrodes on the forehead (Fp1 & Fp2), and then the BioAmp EXG Pill amplifies those signals so that we can detect them and finally send them to the ADC (Analog to Digital Converter) of your Maker. Ultimately, the SpikeSpike Recorder software visualizes signals.

2.6 Prototype Design

EEG is usually recorded non-invasively with electrodes placed on the head, but can also be recorded invasively (mainly for clinical neurological purposes, such as epilepsy) using electrodes placed above the surface of the brain [28].



It Nor mally employs anywhere between 1 and 250 electrodes which is much fewer than neurons, which total about 80 billion. In addition, the skull cannot transmit electricity well which implies that EEG records aggregated activity from large numbers of neurons working together. EEG cannot pinpoint where brain activity occurs because electrodes are placed on the scalp. The cerebrospinal fluid and the brain's coverings conduct electricity well, allowing signals originating from one area of the brain to transmit uniformly. In other words, electrodes placed outside the brain can detect signals from anywhere within it. When considering this, multiple areas of the brain will inevitably be active together or in immediate succession and overlap each other, thus making it clear that signals recorded outside the scalp are a mixture of signals from multiple active parts of the brain, at least generating a strong enough coherent signal to pass through a poorly conducting skull. This is why EEG source localization is classified as an inverse problem (i.e., finding sources inside the head given data from its surface) [29]. The mathematics behind this show that the inverse problem has virtually numberless potential solutions where different combinations of locations and strengths of sources in the brain would cause identical electrical activity patterns at the scalp [30]. This may work effectively, especially for sensory responses like early sensory responses where neural generators are highly important and known (for example, the primary visual or auditory cortex).

Figure 3. EEG signal transmission and data acquisition process. This comprehensive flowchart captures the intricate pathway from the generation of brain signals to their recording and analysis and highlights the essential components involved in the EEG data acquisition process.

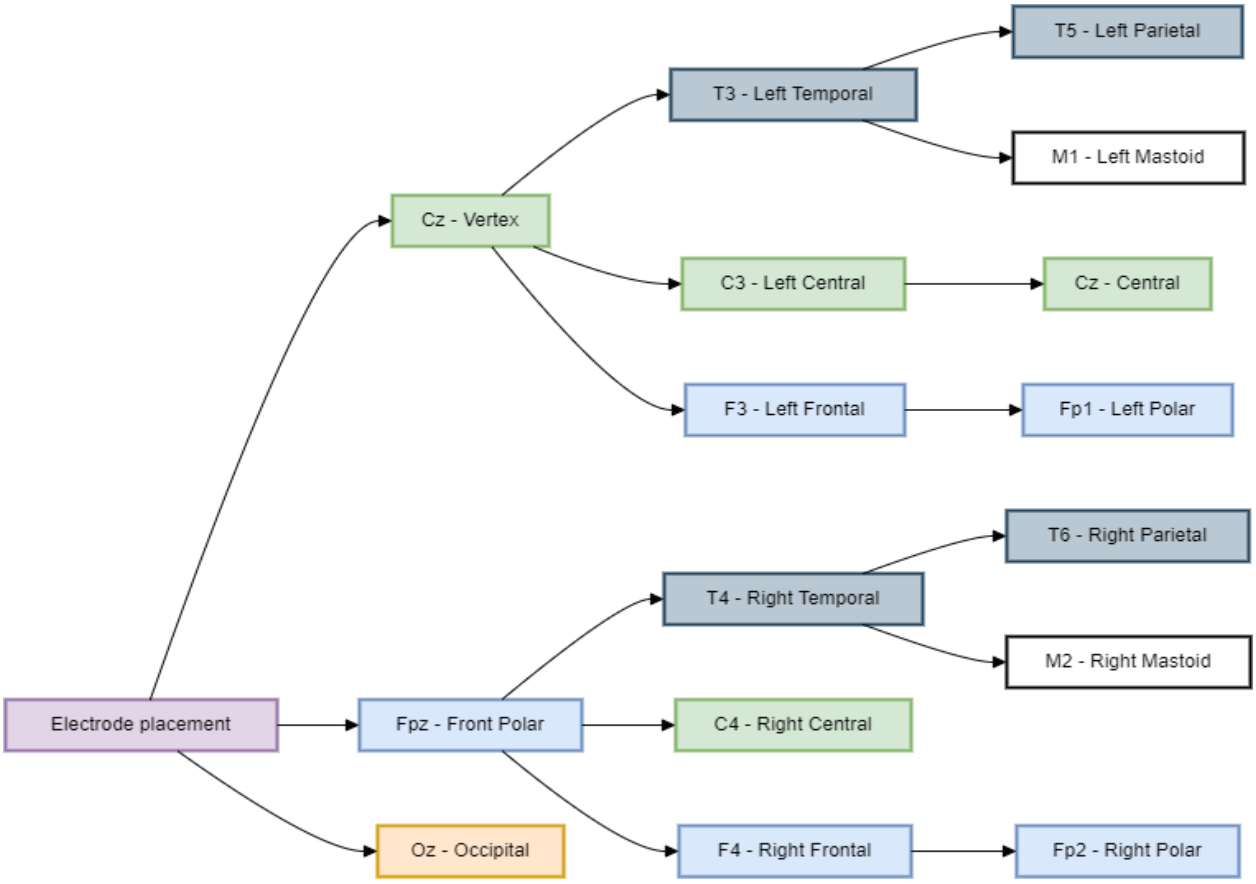


Figure 4. Electrode placement for EEG recording. Placement of electrodes on the patient's head according to the International 10–20 system. These placements are critical for accurately capturing brainwave activities from different regions of the brain.

2.6.1 Signal Recognition

Electrical potentials measured in the EEG may be either positive or negative [31]. It is measured in units of microvolts (μV), that is, thousandths of a volt. This voltage refers to the difference in electric potential between an electrode and a reference electrode situated somewhere else on the head. Depending on what the relative potential is at the reference electrode, the voltage (electrical potential) recorded at each electrode can be either positive or negative. Whether they are positive or negative still suggests brain activation. Taking into account a small section of the cerebral cortex (1 cm square), it contains thousands of neurons, most of which are pyramidal neurons, which are important for cognition. At rest, the interior of a neuron's cell body has a negative potential. This indicates that the axon terminal is more positive than the cell body. Thus, if we placed electrodes in the brain, one close to the cell body and another near the end of an axon, we would record a negative potential at the former and a positive at the latter site. Inputs reaching the neuron's cell body typically induce depolarization, meaning they make it more negatively charged. During EEGs, electrodes are placed on the scalp, and because the head

conducts electric currents effectively, this placement does not significantly alter the recordings. In the case of an electrode positioned directly over the patch cortex, the results would have a positive potential for an electrode put on the opposite side of the head, which will be relatively negatively charged.

As a time-varying signal, the EEG can be viewed, analyzed, and interpreted in two different ways [32]. The first and most common way to view EEG data is in the time domain, with time on the x-axis and intensity (voltage) on the y-axis. The EEG can also be viewed in the frequency domain. This is usually done using a mathematical transformation such as the Fast Fourier Transform (FFT). The FFT is based on the principle that a time-varying (or segmented) signal can be created by summing a set of discrete waveforms with different amplitudes. An electromagnetic wave is a constantly oscillating waveform. Amplitude (the deviation on the y-axis) varies with time and with frequency. Complex EEG waveforms can be described mathematically by combining several electrical waves of different frequencies, each with a larger or varying amplitude. The FFT determines the amplitude of each waveform, and the frequency domain data represents these amplitudes and their frequencies. The results can be plotted in the frequency domain. Here, the frequency is represented on the x-axis and the amplitude on the y-axis instead of time. An important feature of data representations in the frequency domain is the loss of time information. To calculate the FFT and generate frequency domain data, it is not necessary to use the entire time range of the data. In practice, the most common way to analyze EEG is time-frequency analysis (TFA), where power is calculated separately at each frequency of a time series. Another hurdle is that the time domain data may take too long to form a point wave cycle (the time between one peak and another), where two or three shifts are needed [33]. So the length of the data we have determines the minimum time we can determine. This is because it takes longer to complete a cycle. For example, if a sine wave has a frequency of 1 Hz, this means 1 cycle/second while a 60 Hz wave has 60 cycles/second. Therefore, we can resolve a 60 Hz wave in shorter time samples than it takes to resolve a 1 Hz wave. When measuring a specific frequency, longer-time samples provide a better estimate because more samples (changes) are used to measure the frequency.

The relationship between the time domain and the frequency domain is that time domain accuracy is not the same as frequency domain accuracy. Point waves and Fourier transforms are highly important when working with EEG data. One reason is the brain's tendency to produce both activity signals (oscillating brain waves) and aperiodic signals (crests and troughs). The time domain is ideal for viewing and analyzing aperiodic signals, which is the basis of many cognitive neuroscience studies using event-related events (ERP) [34]. However, the frequency domain is better for viewing and analyzing periodic signals.

The brain also tends to use different frequency ranges, called frequency bands, to perform different tasks and carry different signals between brain regions. In general, the activity of each frequency band is relatively independent. So, increased power in the frequency group may show different neurocognitive responses.

Therefore, understanding the conditions under which the EEG was recorded is important for interpreting these frequency bands and where in the head the frequency bands are largest. Most delta waves (Δ) occur during sleep. Alpha waves (A) above the occipital electrodes occur when a person's eyes are

closed (blocking visual stimulation) or bored, but they are also associated with other cognitive processes. Mu waves (M) have the same frequency range as alpha waves but are associated with motor activity (movements of limbs and the body as a whole) and, like beta waves (B), are concentrated in the motor cortex.

2.6.2 Event-related potentials

Event-related potentials (ERPs) are a unique type of measurement derived from EEG data. The EEG is a continuous measurement of the brain's electrical activity, whereas ERPs are short segments of EEG data that are timed to specific events that are needed and are usually determined over several experimental trials. [35] EEG data is recorded continuously throughout the experiment and divided into time-locked epochs (short slices of data) that correspond to events of interest. The event of interest is the occurrence of a stimulus or the occurrence of a motor response (e.g. eye movement). The idea behind ERP is that by matching brain activity to a specific event, patterns of brain activity can systematically occur in response to that event. As mentioned above, EEG is a complex technique because data from all electrodes reflect many sources of noise that can affect the activity of distributed brain regions and the data. By comparing data from multiple trials presenting a stimulus (or a stimulus from a particular test category or situation), we can understand which responses occur systematically in response to the stimulus. We hypothesize that stimulus or non-task-related brain activity and noise do not occur systematically in response to the stimuli. Thus, unrelated and noisy brain activity should be compared, but systematic responses to the stimuli should be observed to determine the extent of OSA. In reality, the signal-to-noise ratio of ERP data increases approximately with the square root of the number of trials included in the data. Depending on the specific ERP effect being investigated, up to 1000 stimuli may be required in each experimental condition to obtain a reliable ERP. The number of stimuli depends on the expected ERP signal size and the difficulty level of the task [36].

Therefore, in a typical ERP experiment, multiple trials are presented in two or more experimental conditions, and results are analyzed across all trials in each condition. Responses occur before or after specific events that trigger ERPs. When the need is related to the response to the stimulus, the focus of the analysis is primarily the ERPs that occur after the stimulus. If the focus is on the motor response, the focus of the analysis may be on brain activity before the response begins. Analysis of ERP data therefore requires segmenting EEG data into short periods of data centered on the experimental session. These time units can vary from hundreds of milliseconds to a few seconds, depending on the duration of the expected effect. Generally, the period includes the time before the start of the event (or after the event if related to pre-event activities). This is a benchmark for comparing brain activity concerning experiments such as our OSA detection design.

2.6.3 EEG analysis

The human EEG has the highest signal strength in the frequency range of 1 to 40 Hz. There is evidence that higher frequencies can convey important neurophysiological information. However, most research questions in most EEG studies, as well as ERP studies, concern EEG signals in the frequency range of 1–40 Hz [37]. The vibration frequency helps identify the source of noise [38]. Small noises are produced by head movement, electrical wiring, head sweat, etc. Low noise occurs when the EEG signal slows

down for a few seconds. However, high-frequency noise can come from sources such as electrical interference and muscle tension (especially facial and neck muscles). High-frequency noises appear as sharp changes in amplitude in the EEG. The frequencies of high and low noise sources overlap with the 1-40 Hz EEG band but are generally either lower or higher than human EEG. This means that by reducing the signal power at frequencies above and below the test

range of interest, the noise and effect on the signal of interest can be reduced. This process is called filtering. Analysis usually occurs at two points in the EEG pipeline [39]. The first occurs when the data is recorded, and the second occurs during pre-processing.

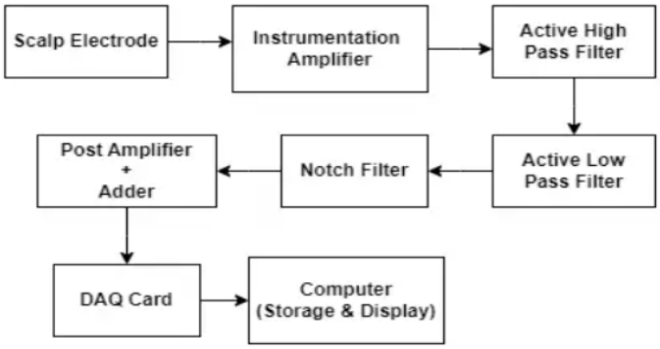


Figure 5. Represents a more in-depth signal processing stage in our prototype design, specifically the software side. Each process is important and plays an invaluable role in visualizing the patient's brain waves.

When collecting EEG data, the EEG amplifier has a filter to block frequencies above a certain threshold. This is called a low-pass filter because the filter passes low frequencies but attenuates (reduces) higher frequencies. Low-pass filtering must be very accurate when digitally recording the EEG (or any signal) due to a phenomenon known as aliasing. This occurs when the high-frequency signal is sampled at a rate lower than the signal frequency, and artefacts (artificial signals that distort the real signal) appear at frequencies lower than the high-frequency source, creating an anomaly. Therefore, aliasing can introduce high-frequency noise as low-frequency artefacts into the data, so low-pass filters should be used.

2.6.4 Pilot study with healthy participants

Two participants, ages 16 and 42, were enrolled in this study. The two participants did not have a body mass index (BMI) of more than 40 kilograms per square meter, were not involved in any type of hypnotic or medication in general, and were free from any cardiovascular diseases. There was no training given to either participant since the study did not require it. The parameters were set as follows: the low bandpass filter was set to 1 Hz, and the high bandpass filter was set to 40 Hz (and 1 HZ to 14 HZ), as we are only recording the EEG signals that range between these frequencies. The 50Hz notch filter will be applied. The threshold was not changed. We viewed the FFT graph as well. The waves were recorded while the participants were awake and asleep. The EEG was recorded in a quiet environment, and the participant was asked to keep still so artefacts and noise were kept to a minimum. It was noticed that although the age difference between the two participants is vast, the waves received

were almost the same amplitude and wavelength. This change, however, arose when the participants were asleep. Although the 16-year-old EEG was mostly uninterrupted and had steady waves, the 42-year-old frequently awoke, and their breathing was ragged. This was, obviously, due to age but was an intermediate differentiating factor between the two EEGs.

Figure 6. Signal for the 42-year-old participant awakening and then laying back down to rest

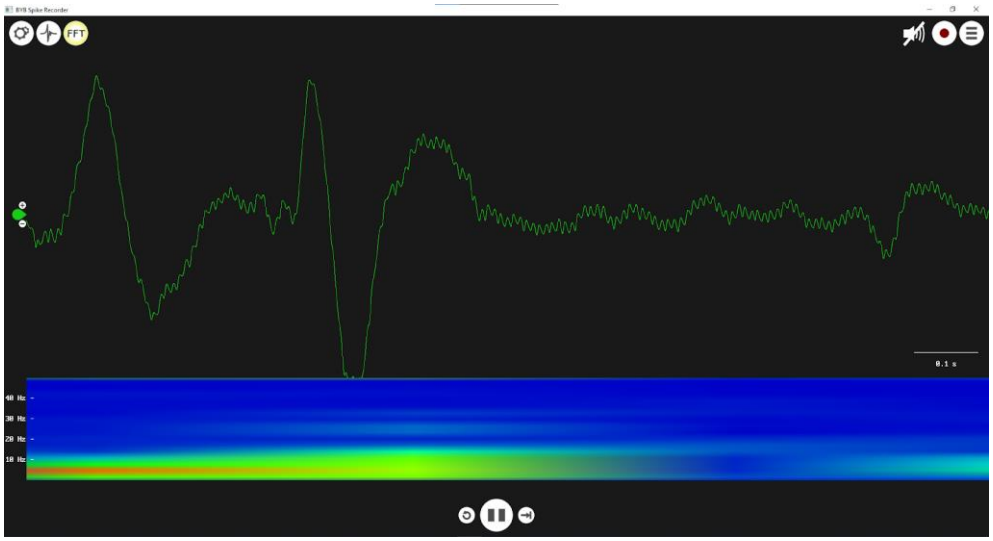
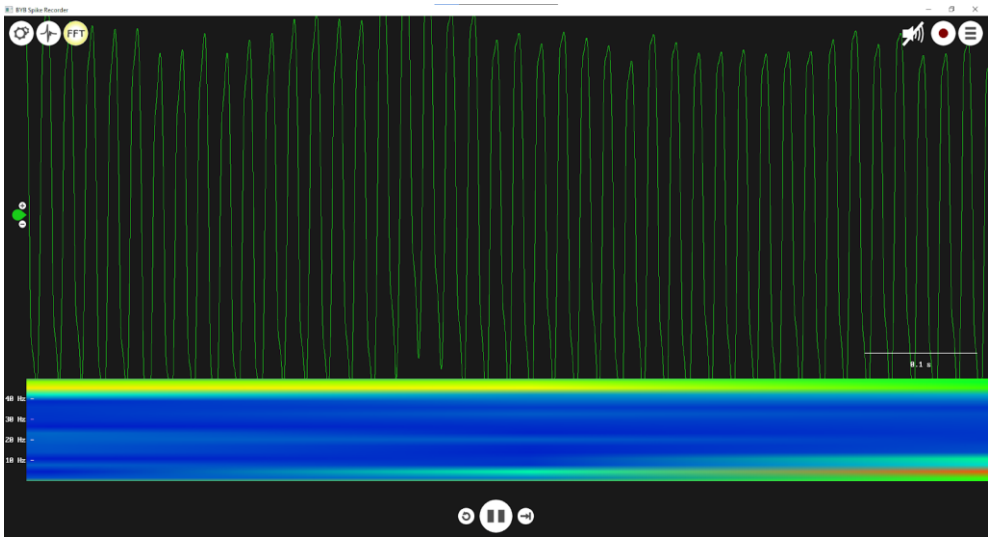


Figure 7. Signal of the 16-year-old participant awake



2.6.5 Nyquist frequency

brain waves are made up of combinations of waves of varying speeds but are all composed of amplitude, phase, and wavelength (or period). The shorter the wavelength, the higher the frequency and so the longer the wavelength the lower the frequency. When we record EEG data, we do it discreetly. While the waves get processed and recorded, it does so at a certain rate which we can not see. We don't see what happens between each wave but only the waves themselves. This implies that if we start to increase

the time taken between each wave, we get a larger gap. We can fill these gaps to a point and this is where the Nyquist frequency comes in. [40]

The highest frequency that can be accurately recorded at a given sample rate is called the Nyquist frequency [41]. It can be set to 1/2 or 1/3 of the sample rate. It is recommended to use 1/3 because it is the safest. Using 1/2 is only acceptable if the components of the noise source can be adjusted easily so that the peaks and troughs are in sync with each other. In real-world situations where the noise is invisible and unwarranted, the 1/3 rule should be used. Most EEG devices automatically filter data as it is recorded using a threshold set by the device engineer to avoid aliasing (also called iterated filtering) [42].

2.6.6 Power Spectral Density (PSD)

We will be using the already defined and set programs created by Python. The raw power of data points is represented in terms of Power Spectral Density (PSD) [43]. Power, in the frequency domain, refers to the strength of electromagnetic waves, and range defines how this power changes with different frequencies. The PSD can be calculated using the FFT method. The data is filtered by using [hi_cut] and [low_cut] as defined parameters. It is a bandpass filter with a high-pass cutoff frequency set at 0.1 Hz and a low-pass cutoff frequency set at 40 Hz. This is done by employing the EEG-ERP extension programmed in the Python language.

2.6.7 Independent Component Analysis (ICA)

EEG uses the term artefact to describe noise in the data that can be attributed to a specific source. So blinks, eye movements, and muscles are included. To be more certain that the results depend on brain activity and not on other components, these components must be removed from the data. The most common physiological artefacts occur at specific times and frequencies [44]. ICA (Independent Component Analysis) is a blind classification system [45]. In other words, you collect hard points and break the math into several other parts. The term “component” here does not refer to ERP components. However, during recording, the individual original signals are mixed to form ICA components. Since each signal has unique spatial and time-related characteristics, discrete component analysis (ICA) can be used to distinguish between EEGs. ICA requires many electronic resources to function efficiently. The maximum number of ICA units that can be removed is determined by the number of electrodes or channels present on the scalp.

2.6.8 Event Codes

In EEG recording, event codes are used to identify the specific event of interest [46]. Normally, every stimulus given to the participant is also sent to the EEG-recording computer through a computer-generated stimulus. Event codes can also indicate other things, such as when a participant has responded or the start of a new trial or condition that does not involve any particular stimulus. Data sharing with ERP relies on these event codes since they are what require the most effort and are most useful in artefact removal.

2.6.9 Support Vector Machine (SVM)

We use Support Vector Machine (SVM) because it is widely used for two-class real-world data classification and is efficient in its performance. It also has the best classification accuracy of 97.14% as compared to the others [47]. These methods are designed to verify and facilitate proper classification by traditional methods. The goal here is to transform the data to higher dimensions to identify the plane that separates these classes from each other. Support Vector Machine (SVM) is the best plan for classifying input data in machine learning algorithms, especially when there are many groups of products in a category. This algorithm was developed to solve only binary classification problems. The main goal of SVM is to split this data into some flat binary classification schemes, and all the different areas are brought together in this process. Above all, capturing all levels of interaction between these components in the context of a training session is the goal of this algorithm.

Figure 8. Represents the signal processing stages in our prototype design. This diagram presents a comprehensive workflow for signal processing in the EEG. The process is divided into several key stages, each playing a crucial role in transforming raw signals into meaningful data.

3. Results

When a ‘dummy patient’ is resting, the prefrontal cortex shows minimal disturbance and is hence visualized as such with delayed constrictions. If a patient with severe OSA were to be in the same position, they would receive incredibly little sleep. This is due to them being interrupted by their throat muscles relaxing, which leads to the blockage of the airway, and this leads to having to sit up straight and breathe naturally rather than on their back or side. The person being in a sudden state of arousal due to low blood oxygen saturation levels causes arousal, which is a basic state of being awoken or our sense organs being awoken to the point perception, which causes a spike in the EEG. This is visualised on the Spike Recorder screen as a sudden spike for the normal waves. Models such as the one used in Arduino recommend that prefrontal pathways can choose pertinent signals over distractors in patients with OSA.

4. Discussion

PSG, widely considered the gold standard test for diagnosing OSA, gives results that help prevent and treat the chronic disorder. Rapid solutions with more accuracy are possible with the steady increase in machine learning and improvement. This helps in choosing the best type of therapy that a patient would need, keeping their characteristics and circumstances in mind. A PSG, however, possesses several complications, like being very time-consuming costly, and not so portable, unlike the newer technologies like newer CPAP treatments, which is why methods such as ‘HSAT, although not as informative as PSG, and CPAP, which are considered effective treatment options for moderate to severe OSA.

There are some other methods, like using hypnotics, and this does show promising effects. Further studies can be done to make it more versatile, and it has also been proven to reduce OSA severity. However, it requires a very specific and targeted approach, and it has been shown to not have affected

pharyngeal muscle activity, though a concern about hypnotics is the prolongation of respiratory effects and the worsening of hypoxemia. This applies specifically to people with a high threshold for respiratory arousal responses. Another very specific method and one that people barely use is BiPAP. Just like CPAP, it's also another APAP (Automatic Positive Airway Pressure), but what separates it from CPAP is that the BiPAP makes it much easier to breathe because it uses higher pressure during inhalation and lower pressure during exhalation, making breathing much easier for the patient, unlike in CPAP, where the pressure gradient is constant. Some people with sleep apnea or similar breathing problems may use a CPAP first. But in some cases, a BiPAP may be a better choice if you need more help breathing because of severe sleep apnea or a condition like congestive heart failure. BiPAP is also used normally in highly specialized cases if the patient has OSA along with congestive heart failure or some cardiovascular condition. Plus, it also has a much higher range than that of the CPAP.

As mentioned earlier, the signals from the BackyardBrains Spike Recorder screen originate from the prefrontal cortex part of the patient's brain, and then the BioAmp EXG Pill amplifies those signals so that we can detect them and finally send them to the ADC (Analog to Digital Converter) of the Maker. Ultimately, the SpikeSpike Recorder software visualizes signals in the form of waves, which helps in understanding if there is a sudden disturbance within the patient's cortex.

When a person is sleeping, due to an interruption in breathing, carbon dioxide may build up in the bloodstream while the oxygen saturation in the blood decreases. When the concentration of CO2 reaches a certain point, it's detected by chemoreceptors. These receptors trigger an alarm in the brain, which leads to the person waking abruptly and breathing heavily. As a result, a transition in sleep stages occurs, which in turn causes oscillations in the exertion position of the colourful frequency bands of the EEG signal. Hence, further distinct features can be saved in frequency band-limited signals for apnea discovery compared with those in full-band EEG signals [48]. As a result, for apnea event discovery, characteristics of band-limited signals are used rather than analyzing full-band EEG signals. The EEG signal is partitioned into five frequency bands, including delta (δ) (0.25–4 Hz), theta (θ) (4–8 Hz), alpha (α) (8–12 Hz), sigma (σ) (12–16 Hz), and beta (β) (16–40 Hz) [49]. Spectral filtering is done using the fast Fourier transform, which is a computational tool that transforms time-domain data into the frequency domain by deconstructing the signal into its parts: sine and cosine waves.

In short, we have promising ways to treat OSA, but we are still a long way from fully curing it and making it a thing of the past. There is promising research as we are finding ways to diagnose it better and newer technologies to treat and manage it.

5. Conclusion

Obstructive sleep apnea syndrome is a growing health concern, affecting nearly one billion people worldwide. It is an independent cardiovascular risk factor associated with incident obesity, insulin resistance, hypertension, arrhythmias, stroke, coronary artery disease, and heart failure. Obstructive sleep apnea-related cardiovascular and metabolic comorbidities are a major concern for the prognosis and the complexity of obstructive sleep apnea-integrated care. Continuous positive airway pressure, the first-line therapy for the treatment of obstructive sleep apnea, is highly effective at improving symptoms and quality of life but has a limited effect on co-morbidities. This study explores the physiological phenomenon behind OSA, how it affects people, how dangerous it is, how to diagnose it, and how to cure it. The characterization of the different causes or phenotypes of OSA in recent years has provided

new pathways for targeted therapy, which reduces manpower and resources and makes the treatment much more time- and cost-efficient for both the patient and the doctor. New, simplified approaches to estimating each of the key causes of OSA have recently been developed. While more work is required, particularly directed toward the impaired pharyngeal muscle trait, these new tools offer promise for the translation of detailed phenotyping concepts to the clinic. Identification of the traits also provides insight into which patients are more likely to develop specific disease consequences of OSA and who will not help decide who needs immediate care and who doesn't [50]. However, it seems important to explore new mechanisms, such as those involved in mitochondrial homeostasis, and perhaps to study in detail the interactions between these different key players. This could lead to the identification of new biomarkers of cardiovascular risk in patients with OSA and/or the proposal of new therapeutic targets, in addition to or instead of the current treatment. While there has been substantial research on the role of OSA as an independent risk factor for comorbidity, the reverse relationship has been less well-studied and represents an important area for future research. The author's assessment of the putative bidirectional relationships between OSA and comorbidities.

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Author contributions
S.L. writing - original draft, writing - reviewing and editing, conceptualization, data curation, methodology. S.K. writing - original draft, writing - reviewing and editing, conceptualization, data curation. H.B. writing - original draft, writing - reviewing and editing, conceptualization, data curation, methodology.

Competing financial interests
The authors declare no competing financial interests.

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Authors

Sean Lennon is in the 11th grade in Narayana Kuvempu Bhavan with a combination of PCMB. He wishes to help the world in any way he can and has chosen the medical path. He enjoys movies, video editing, and playing sports.

Srushti Kulkarni is in the 12th grade, studying at Sharnbasweshwar PU College with the stream PCMC. She likes singing and reading books and she has an interest in coding. She wishes to pursue Computer Science and develop apps. She has recently published a review article on CMUT Technology in the International Journal of Science and Research.

Harshith Bandaru is in the 11th grade at DPS Hyderabad with the stream MBiPC. He has decided to give back to society by serving people as a surgeon. He likes to spend his free time singing, watching videos, writing stories, and playing video games.