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PREDICTING SLEEP STAGES WITH MACHINE LEARNING AND WEARABLE BYTEFLIES SENSOR DOTS: A PILOT STUDY

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ABSTRACT

The conventional method for quantifying sleep is through the use of Polysomnography (PSG) and a trained human sleep scorer by observing and evaluating the output in 30-second epochs. A PSG device can be rather invasive to one's regular sleep pattern and therefore can potentially result in irregular sleep patterns. Furthermore, human sleep scoring classification by a trained expert can be rather time consuming and subject to inter/intra rater variability. Nevertheless, human sleep scoring with PSG still remains the gold-standard for sleep measuring and classification for the diagnosis disorders related to sleep. The present pilot study explores the possibility of using a wearable device known as a ByteFlies Sensor Dot to measure signal activity from an individual during a night's sleep. This validation study focuses on the signal capture of alpha frequency band through a phenomenon known as "the Berger effect." Participants will be asked to open and close their eyes while being connected to the gold standard PSG device and exploratory ByteFlies Sensor Dot device. The resulting alpha signals will be identified with a machine learning algorithm for cross comparison and analysis. In conclusion, the validation study will discuss methods to improve on the measuring of EEG and sleep stage scoring with the ByteFlies Sensor Dot for sleep monitoring and sleep disorder diagnosis.

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LIST OF ABBREVIATIONS

AASM .... American Academy of Sleep Medicine

AAST .... American Academy of Sleep Technologists

AHI .... Apnea Hypopnoea Index

BST .... Beddit Sleep Tracker

CI .... Confidence Interval

ECG........ Electrocardiogram

EEG........ Electroencephalogram

EOG .... Electrograms

EMBC .... Engineering in Medicine and Biology Society

EMG........ Electromyograms

GPS .... Global Positioning Satellite

Hz........ Hertz

IEEE........ Institute of Electrical and Electronics Engineers

OSA........ Obstructive Sleep Apnea

N1 .... Non-REM Stage 1 Sleep

N2 .... Non-REM Stage 2 Sleep

N3 .... Non-REM Stage 3 Sleep

PGO........ Ponto-Geniculo-Occipital

PSG .... Polysomnography

REM........ Rapid-Eye-Movement

SAS .... Sleep Apnea Syndrome

SNR ....Signal-to-Noise Ratio

SWS ....Slow-Wave Sleep

INTRODUCTION

What is Sleep?

Sleep is a condition in which the body and mind becomes relatively inactive, relaxed and unconscious. It occurs at regular intervals and is typically regulated by the body (Borb & Achermann, 1999). Sleep is essential for all human beings and deficiency or disruption to adequate efficient quantities of sleep can cause severe mental and emotional complications (Killgore, 2010). In extreme cases, where sleep deprivation continues for several weeks, the results can be significantly harmful and could result in death from infections or tissue abrasions (Rechtschaffen & Bergmann, 1995). Sleep is critical to the physical and mental well-being of the human body. The body must rest for the necessary length in order to properly function and survive.

There are two main phases of sleep that occur during a typical human nocturnal sleep cycle. These two main sleep phases include rapid-eye-movement (REM) sleep and slow-wave sleep (SWS) or non-REM sleep. SWS is recognized by slow high amplitude electroencephalogram (EEG) oscillation while REM sleep is described as fast low-amplitude wave oscillation with an EEG. SWS primarily occurs during the early part of the sleep cycle and decreases in both intensity and duration as the sleep period continues. REM sleep on the other hand is typically more intense and extensive toward the end of the sleep phase. During a night's sleep, the body will alternate in a cyclic manner between REM and non-REM sleep phases (Rasch & Born, 2013).

Interestingly, both non-REM (SWS) and REM sleep can be further divided into sub-categories. Non-REM sleep can be further separated into N1 (non-REM 1), N2 (non-

REM 2), and N3 (non-REM 3) which represents a gradual advance into deeper stages of sleep (Liang, Shih, Chen, & Kuo, 2019). Non-REM sleep is typically characterized by a decrease in metabolic rates and muscle tone. These physiological characteristics reach their lowest rates during SWS (Purves et al., 2001) and during this time the brain begins to consolidate memories (Rasch & Born, 2013). Debatably, REM sleep is the most important sleep stage as it is shown to have a rapid change in brain activity with aspects of memory consolidation and dreaming. It is a critical step for the body feeling recharged and fully alert for the following day. Typically, REM sleep begins 90-120 minutes after initially falling asleep (Peever & Fuller, 2017) and increases in duration as an individual progress to the later stages of sleep (Rasch & Born, 2013). Furthermore, electrophysiological features of REM sleep include the desynchronization of cortical EEG, hippocampal theta waves and ponto-geniculo-occipital (PGO) waves. Ironically, the desynchronization or irregular brain wave activities (compared to non-REM sleep) in EEG observed in REM sleep resembles that of wakefulness (Héricé, Patel, & Sakata, 2019). The detection and understanding of the various periods of sleep are critical to monitoring sleep. This information is critical to understand sleep complications and assist in the selecting of upon treatment.

Polysomnography as the Gold Standard

Currently, the most valid method for detecting sleep stages is done with Polysomnography (PSG). Recordings with PSG are typically done during an overnight sleep and include the capture of EEG, electrograms (EOG), and electromyograms (EMG) in which real time data can be conveyed. The current gold-standard for measuring and evaluating data from PSG is done by an expert human scorer in accordance with guidelines from the American Academy of Sleep Medicine (AASM). Other established guidelines do exist however, the AASM is considered the conventional method. The AASM standard scoring method classifies signals into 30-second epochs from a dataset for interpretation. The AASM classifies sleep stages into W (wake), N1, N2, N3, and REM sleep (Rosenberg & Hout, 2013). The classifications can be summarized in Table 1 (Iber, Ancoli-Isreal, Chesson, & Quan, 2007).

Table 1: Sleep Stage Classification Summary.

Classification	Criteria
Wake (W)	First stage before falling asleep. EEG signals are rapidly changing and alpha waves are present for more than 50% of an epoch.
Non-REM Stage 1 (N1)	First stage after stage W. Alpha waves are replaced by low amplitude (theta waves) with mixed frequency activity for more than 50% of an epoch.
Non-REM Stage 2 (N2)	EEG amplitude becomes higher. Sleep spindles and K-complexes appear during this deeper stage of sleep.
Non-REM Stage 3 (N3)	20-50% of EEG signals are delta waves and slow-wave sleep (SWS) are present.
REM	Presence of both alpha and theta waves. Eye movement is rapid, irregular and sharp. Sawtooth waves present.

PSG Limitations

Despite the PSG's current capabilities, a PSG device is sizable and has numerous attachments that are placed on the participant's body for monitoring. Furthermore, sleep studies with PSG are typically done at a sleep center outside of the typical sleeping environment of the participant being tested. These tests are typically expensive, time consuming for both the individual being tested, and impractical for long-term use especially if in-laboratory recording is necessary. These limitations associated with PSG certainly impact the participant's sleeping pattern which can in turn impact the results of the test and classification of sleep stages. For this reason, "less invasive" methods of sleep monitoring have been in development (Zambotti, Baker, & Colrain, 2015). These techniques and devices have focused on being "user friendly" and allowing for the monitoring of sleep of an individual while being in the comfort of their own home and bed.

Sleep Scorer Limitations

Furthermore, the scoring and classification of sleep stages is accomplished by a "well-trained human expert." This process is rather time-consuming, subjective and limited due to the constraints of using 30-second epochs for stage classification. Epochs lasting 30-seconds in duration run the risk of missing short-lived events like arousal, movement and respiratory issues that are associated with sleep disorders. Fragmenting sleep into 30-second epochs can therefore result in less reliable sleep stage classification (Schulz, 2008). Moreover, the classification of sleep stages is based on the proper identification of frequency waves located within the epoch. In turn, this may result in the misclassification of sleep stages, inter/intra scorer variability and possible misdiagnosis of general sleep quality. Overall, the AASM reported an overall agreement for interscorer reliability of 82.6% for sleep scoring professionals (Rosenberg & Hout, 2013). More recently, machine learning has been introduced as a method for sleep scoring.

Deep learning, a branch of machine learning, has shown promise with the use of neural networks to derive sleep stages through decision tree algorithms with hierarchical features from imported datasets. Interestingly, some automatic sleep scoring methods can reach an agreement of greater than 82.6% but the standard method for scoring sleep still continues to be a manual process. This is because the methodology in which machine learning classifies and scores sleep is still poorly understood (Liang, Shih, Chen, & Kuo, 2019).

Introducing the ByteFlies Sensor Dot Device

The ByteFlies Sensor Dot is a small, wireless and wearable device that allows for the monitoring of vital signs of the individual wearing the device. This device allows for the monitoring of signals typically captured with PSG but are significantly smaller in size and may be able to monitor sleep in a minimally-invasive manner compared to a typical PSG device. The ByteFlies Sensor Dot allows for continuous monitoring and the collection of data from the wearers own bed. The device takes only about 3 hours to be fully charged and can record for a continuous 24 hours. This allows for the monitoring during an entire night's sleep. The ByteFlies Sensor Dot is interfaced with the Sensor Patch and biopotential electrodes to capture signals of interest. As many of these Sensor Dots and Patches can adhere and be worn on the body to capture signals simultaneously depending upon the signal of interest (ByteFlies, 2019).

Limitations of the ByteFlies Device

Despite the promise of the ByteFlies Sensor Dot device, there are limitations associated with the device. The ByteFlies Sensor Dot device itself has a biopotential amplifier sampling rate of 250 Hz per channel for EEG, EMG, and electrocardiogram (ECG) recordings (ByteFlies, 2019). However, according to the American Association of Sleep Technologists (AAST), the desirable sampling rate for these channels is 500 Hz but they can operate at a minimum of 200 Hz (2012). In addition, a typical PSG device can monitor EEG, EOG, EMG, ECG, airflow, respiratory effort and blood oxygenation (Corral-Penafiel, Pepin, & Barbe, 2013). Whereas a Byteflies Sensor Dot can only monitor EEG, EOG, EMG and ECG. Furthermore, the ByteFlies Sensor Dot lacks a user interface on the Dot itself for control. This means that the ByteFlies Sensor Dot is physically controlled by placing it in the Docking Station for charging, downloading or viewing a recording and starting a recording. Therefore, real time feedback and data examination is not possible with ByteFlies Sensor Dot. The ByteFlies Sensor Dots must be placed on the Docking station at one time for downloading and charging (maximum of 5 at one time). Although, the temporal alignment of multiple ByteFlies Sensor Dots is rather difficult as synchronization between more than one ByteFlies Sensor Dot is not possible upon placing on the user's body. Recordings will begin as soon as the ByteFlies Sensor Dot is removed from the Docking Station (ByteFlies, 2019).

Ambulatory PSG

Ambulatory PSG devices have been developed as an alternative monitoring device for portable recording and classification of sleep from home. The primary development of this device was to effectively monitor individual's with Obstructive Sleep Apnea (OSA). Although, this portable PSG has allowed for increase accessibility to PSG monitoring it has provided some insights into limitations for home sleep monitoring devices. Unattended portable monitoring devices are susceptible to data loss from equipment malfunction or disconnection, patient/user noncompliance, and limitations in diagnostic qualities (Corral-Penafiel, Pepin, & Barbe, 2013).

The Berger Effect

The "Berger Effect" was first observed unexpectedly in which the opening of closed eyes resulted in the EEG oscillations in the alpha band (8 – 13 Hz) decrease in amplitude or completely diminish. Berger initially predicted that the opposite effect would occur in which the stimulus would result in an EEG oscillation with a larger amplitude. This phenomenon is often referred to as "alpha blocking" and was first observed by Hans Berger in 1933 (Berger, 1933 & Kirschfeld, 2005). The "Berger Effect" is often considered for key feature for identification and extraction during EEG analysis. This is because the alpha wave amplitude during the eyes closed versus open is often observed as an increase in power (Grummett et al., 2015). Significant change in alpha amplitudes is reflective of the device having the efficient signal quality capturing abilities (Radüntz, 2018). In addition, the alpha wave feature is considered a pivotal indicator for the induction of sleep and is related to the rhythm found Non-REM sleep stage(s) at the beginning of sleep (Kim, Lee, Jang, Kwon, & Park, 2013).

Thesis Statement

Despite the benefits associated with the ByteFlies Sensor Dot, further investigation is required to understand its full potential. The presented study will investigate the sensitivity of the ByteFlies Sensor Dots compared to the “gold standard” PSG by measuring alpha wave signal changes as associated with eyes closed versus open (the “Berger Effect”).

METHODS (research-based)/**PUBLISHED STUDIES** (lit-based)

Participant Set-up

Participants will be fitted and monitored with electrodes from an EEG device as presented by Grummett et al., 2015 and then the electrodes from the ByteFlies Sensor Dots. Electrodes from EEG devices will be placed for recoding in standard 10-20 EEG layout. Visual and written instructions will be provided to participants prior to the start of the task (Grummett et al., 2015).

Electrode Considerations

The type of electrode used for signal capture is important for yielding a high signal-to-noise ratio (SNR) during EEG monitoring. The current gold-standard for EEG systems is conventional wet electrode system which results in low impedance levels during recording. However, the use of adhesive conductive gel for wet electrode use during EEG recordings is expensive, time consuming, and not feasible for lengthy at home use (Hinrichs et al., 2020). Despite the benefits associated with dry electrodes, it has been argued that these systems may have a higher scalp-to-electrode impendence compared with wet systems and are more susceptible to electromagnetic interference. However, the impendence can be mitigated through the use of active electrodes to pre-amplify signal and applying multiple pins to make additional contact with the scalp (Grummett et al., 2015). As an example, in a validity study with EEG systems that had both "wet" and "dry" electrodes by Hinrichs et al (2020), the authors reported that Alpha and Beta powers during rest did not statistically differ ($p > 0.05$) in all cases.

Furthermore, the participants reported a preference to wearing the dry electrode headset systems (Hinrichs et al., 2020).

Eyes open/closed; the Berger Effect Task

Participants will complete the eyes open/closed task for the Berger effect as suggested by Grummett et al (2015). The resulting EEG signal will be a rather high amplitude alpha wave during the eyes closed event compared to the eyes open event. The task will require participants to stare at a cross in the middle of the screen for 30-seconds to promote concentration. The participants will be instructed to minimize eye blinking and movement during the eye open task to minimize background noise signal capture. Following the eyes open task, participants will be asked to close their eyes. During the eyes closed task, participants will be asked to keep eyes as still as possible to avoid eye movement for 30-seconds (Grummett et al., 2015).

Data Processing and Analysis

All data will be recorded with a sampling rate of 250 Hz which is the lowest sampling rate across the systems. A band-pass filter will be applied for the alpha frequency for signal isolation (Radüntz, 2018). The alpha frequency will be defined as 8 – 13 Hz with 1 Hz resolution as defined by Grummett et al (2015). A Butterworth band-pass filter will be applied in Python using SciPy (Weckesser & Morderca, 2012). Python is a programming language that is typically used for scientific computing. SciPy is an available toolkit or package for Python that can perform statistical functions (Pedregosa, et al., 2011). EEG data that is captured during breaks and instructional periods will not be used for analysis of filters (Grummett et al., 2015).

Statistical analysis will be calculated with a 95% confidence interval (CI) ($p \leq 0.05$) value for both data from PSG and ByteFlies. Differences between the power of alpha band frequencies with PSG and ByteFlies will be compared with paired *t tests* and Bland & Altman (1986) as calculated in Zambotti, Baker, & Colrain (2015).

RESULTS

Previously Published Validation Results

Understandably, other consumer grade sleep monitoring devices have resulted in varying results when compared to the gold-standard PSG. The Beddit Sleep Tracker (BST) is a particular device that may not have similar sleep detection capabilities as PSG. Tuominen, Peltola, Saaresranta, & Valli (2019) yielded results from a validation study of the consumer grade BST and PSG during sleep in which the BST was unreliable for measuring sleep in adults. The device has difficulty accurately measuring total time spent sleeping, wake after sleep onset and the discrimination between non-REM sleep stages and detecting REM sleep . Overall, the results from this study challenges the validity of using BST to monitoring sleep (Tuominen, Peltola, Saaresranta, & Valli, 2019).

However, not all consumer grade sleep monitoring devices have resulted in inadequate signal detection when compared to PSG. The Jawbone UP fitness tracker has shown promise as a potential monitor for sleep. In a validation study in which the authors simultaneous collected sleep data from the Jawbone UP and PSG device, the outcomes resulted in positive agreement with both devices. In similar measurements to Tuominen, Peltola, Saaresranta, & Valli (2019), the authors of Zambotti, Baker, & Colrain (2015) showed relatively accurate correlations when measuring total time spent sleeping, wake after sleep onset and sleep efficiency in adolescents. Overall, the results of the Jawbone UP and PSG validation study showed relatively good agreement between the two devices but further validation testing is necessary.

PSG and ByteFlies Sensor Dot Valued Results

Based off of the previously conducted research, the results that are expected would show a significant correlation between the power of alpha band frequencies with the gold-standard PSG device and the ByteFlies Sensor Dot. Statistically, this means that the observed p-value from the paired *t test* would result in a p-value ≤ 0.05. However, if the ByteFlies Sensor Dot was unable to accurately identify alpha band frequency changes when compared to PSG, then the results of the paired *t test* would show a p-value >0.05

Summarized Drawbacks of the ByteFlies Sensor Dot Device

The primary drawbacks associated with the ByteFlies Sensor Dot device are the reduced biopotential amplifier sampling rate of 250 Hz per channel for signal capture and the inability to synchronize recordings with multiple ByteFlies Sensor Dots. In addition, the ByteFlies Sensor Dot does not allow for real-time data analysis as it has to be placed on Docking Station for data upload and analysis (ByteFlies, 2019).

DISCUSSION

Discussion of Previously Published Validation Results

The results presented from previous validation studies between the gold-standard PSG device and novel consumer grade sleep monitoring device have yielded both promising and contrasting results. The BST device resulted in poor correlations between with the gold-standard PSG device. Therefore, the authors (Tuominen, Peltola, Saaresranta, & Valli, 2019) recommended that this device not to be used for measuring and classifying sleep. However, it is important to note that this device is not wearable and therefore is not placed on the body for close monitoring. In fact, this device is placed under the mattress to monitor sleep and furthermore lacks an application to sleep REM classification (Tuominen, Peltola, Saaresranta, & Valli, 2019). The design limitations of the device and software may have resulted in poor results when monitoring sleep.

On the other hand, Zambotti, Baker, & Colrain (2015) showed more optimistic results with the Jawbone UP device when compared to PSG. The authors of this validation study presented results that had overall positive agreement between PSG and the Jawbone UP device for measuring total time spent sleeping, sleep efficiency and wake after sleep onset. It is however important to note that the authors only monitored one night of sleep and observed adolescence. This is because sleep in general can be highly variable from night to night and differs depending upon age. Similar to the ByteFlies Sensor Dot, this device is worn on the body for monitoring but as fitness tracker for actigraphy monitoring worn on the wrist (whereas ByteFlies uses EEG and electrodes adhesively placed on the body for monitoring). Despite the positive results, the authors did acknowledge that further validation is needed with the device before supporting it as an inexpensive alternative to measure sleep both a home and research setting. Despite the two previously presented research studies provided varying results for monitoring sleep, the ByteFlies Sensor Dot may be more advantageous when measuring alpha wave frequency changes precisely as the device is applied directly on the body.

Solutions for ByteFlies Limitations

Despite the promise of the ByteFlies Sensor Dot device, there still are limitations associated with the device. The current recording initiating mechanism results in desynchronized temporal alignment prior to the start of the recording. This desynchronization calls for a manual synchronization by a user such as a " signal trigger" when all 5 devices have started recording. This signal trigger may be mechanical or physical such as a shake or jump to create a large signal indicating the start of the study (Khan, 2020). This limitation calls for improvement within the current capabilities of the ByteFlies device and software itself. A simple solution may be to include a start and stop recording button on the ByteFlies Sensor Dot itself or on the Docking Station synchronized to the ByteFlies Sensor Dot via Bluetooth.

Some investigation has been done to use a system which has the capabilities to synchronize multiple devices onto one timeframe to measure multiple signals. Yokota, Soshi, & Naruse, (2019) developed a wireless data-recording system in which EEG signals can be extracted within the same timeframe of a video game stimulus. The authors used Global Positioning Satellite (GPS) signals to synchronize systems with an EEG device and external input device that can retrieve signal and synchronize between the two devices. The recorded signal included time information which included a time-stamp for each signal which could be accurately recorded with millisecond resolution. The experimental GPS-EEG device was attached to a wearable headset which was worn by the participant (Yokota, Soshi, & Naruse, 2019). Integration of GPS synchronization technology presented by Yokota, Soshi, & Naruse, (2019) with the ByteFlies Sensor Dot may be a workable solution to the signal capture to the five separate signals being captures with the ByteFlies Sensor Dot. However, the wearable headset does pose an issue for at home comfort and feasibility and therefore would need to integrated into the ByteFlies Sensor Dot prior to implementation. Thus, further larger-scale studies may be required to investigate the validity of signal capture with the ByteFlies Sensor Dot and accessing the captured data in real time prior to integrating this technology into the ByteFlies Sensor Dot system.

Reducing Epoch Length

Currently, the gold-standard for classifying sleep from PSG is with 30-second epochs. Sleep scorers have been fundamental limited by extensive epoch duration. The 30-second fixed epoch length has been used because after 30 centimeters the paper containing the recording which corresponded to 30-seconds was cut as presented in Loomis, Harvey, & Hobart (1938). With the introduction of machine learning algorithms into sleep scoring, some researchers have called for a change in this duration for sleep scoring classification. As previously discussed, epochs lasting extensive periods (i.e. 30-seconds) run the risk of missing short-lived events which can be associated with sleep disorders therefore resulting in less reliable sleep stage classification and diagnosis (Schulz, 2008). Furthermore, machine learning algorithms may allow for the shortened processing times for sleep stages yielded by the increased number of epochs when reducing epoch length. The use of automatic sleep scoring has become increasingly popular in a research setting despite the continued use of human scoring from a clinical perspective. Dimitriadis, Salis, & Linden (2018) explored a novel approach to automatic sleep scoring classification by using a fast and efficient single EEG-sensor. The technique relied on dynamic reconfiguration of different aspects of cross-frequency coupling estimates which resulted in rather high classification accuracy of $94.4 \pm 2.2\%$ on their collected data. Interestingly, the authors decided to introduce a novel epoch segment length of 5-seconds for EEG recording analysis in addition to performing automatic sleep scoring classification without EOG, EMG, and ECG recordings typically associated with PSG recordings. Furthermore, Dimitriadis, Salis, & Linden (2018) were able to achieve high classification accuracy on external open source sleep database of 77 subjects $94.0 \pm 2.9\%$. This external validity may provide insight for possibly using single EEG-sensor automatic sleep scoring classification on other data sources similar to the data found with the ByteFlies Sensor Dot. The proposed methodology of using 5-second epochs for assignment instead to the standard 30-second may warrant a consideration for changing the epoch length for sleep stage classification as this could have influenced the results in higher classification accuracy. Furthermore, this time reduction may result in more exact sleep stage classification in which epoch times are 1 millisecond and not limited by human sleep scorers.

Although, the reduction in epoch length may improve sleep classification it does pose some inherent drawbacks. With shorter epoch lengths during a night's sleep, the number of data points requiring sleep stage classification would increase. Therefore, creating more dependencies for data processing with machine learning and advanced computing technology to complete data processing. In addition, advanced computing technology often costs more money.

Possible Benefits of the ByteFlies Sensor Dot as a Monitoring Device for Disorders

Devices like the ByteFlies Sensor Dot can allow for personalized medicine for sleep disorders similarly to other areas of healthcare. Sleep apnea syndrome (SAS) is a common sleep-related breathing disorder in which an individual experiences partial or complete respiratory discontinuation during sleep. Unfortunately, SAS has been diagnosed all around the globe and tends to effect men more than women. Those who suffer from SAS tend to be more likely to suffer from cardiovascular problems like hypertension, stroke and heart failure compared to those without SAS (Malhotra & White, 2002). Moreover, those afflicted with severe SAS can have decrease memory and cognitive function (Durmer & Dinges, 2005). SAS can be diagnosed by a medical specialist and is often done with the Apnea Hypopnoea Index (AHI). This involves the monitoring of an individual during a night's sleep (Guilleminault, Tilkian, & Dement, 1976). In-laboratory PSG is still considered the gold-standard for evaluating SAS.

However, as previously discussed, in-laboratory PSG devices can be invasive, expensive, and unfit for prolonged sleep monitoring for an individual undergoing a sleep study. For this reason, the typical quality of sleep may be impacted by the device itself. Portable PSG devices have been introduced to evaluating and monitoring SAS. Yet, results obtained from these portal devices may be less accurate than those obtained by an in-laboratory device (Corral-Penafiel, Pepin, & Barbe, 2013). Nevertheless, the ByteFlies Sensor Dot is significantly smaller in size compared to in-laboratory PSG device and does allow for continuous monitoring of sleep from the comfort of one's own home. Consequently, it may want to be considered as an option for at home EEG monitoring of SAS and other sleep disorders.

CONCLUSION

In conclusion, the ByteFlies Sensor Dot may provide additional insight into personalized medicine through wearable EEG monitors during sleep. Despite its current limitations, the device may provide insight for monitoring sleep accurately as a low-profile consumer grade device for at home use. Additionally, it can potentially illustrate the ability to successfully apply common machine learning algorithms through programing languages like Python to successfully classify sleep stages at a more precise time duration. For future studies, it will be important to address the limitations and findings associated with this pilot study and the ByteFlies Sensor Dot device. Furthermore, it will be essential to incorporate machine learning algorithms for sleep stage classification during future ByteFlies Sensor Dot sleep studies. Moreover, it will be important to explore the potential benefits of using reduced epoch lengths with data collected from the ByteFlies Sensor Dot to classify and more accurately monitor sleep. The idea of developing personalized treatment plans with minimally invasive EEG monitoring may be possible with the ByteFlies Sensor Dot.

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CURRICULUM VITAE

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