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PERSONALIZED SLEEP SIGNATURE: A NOVEL APPROACH TO UNVEIL PAEDIATRIC SLEEP BEHAVIOUR WITH TRANSFORMER ATTENTION MECHANISM AND GRAPH ATTENTION NETWORKS

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ABSTRACT

Sleep disorders manifest differently across individuals, making accurate diagnosis and treatment highly complex. Even within the same diagnosis, there can be variation in sleep architecture among patients, which makes generalization across people difficult. Traditional sleep analysis methods rely on manual scoring and fixed diagnostic criteria, which fail to capture subject-specific variability in sleep patterns. To address this, we propose a data-driven Personalized Sleep Signature (PSS) approach that learns individualized sleep behaviour using AI models. This study introduces the PSS framework, combining Transformer-based Attention and Graph Attention Networks (GATs) to model nuanced sleep characteristics. We utilize the Nationwide Children's Hospital Sleep Data, a paediatric Polysomnography (PSG) dataset containing EEG and physiological parameters such as ocular movements, EMG activity, blood pressure, and respiratory rate. From this, we extract sleep epoch features and demographics to form Sleep Signature Groups that reflect common behavioural patterns. Unlike conventional classification, our method captures personal variability and delivers individualized sleep hygiene guidance. The model achieved 94% accuracy in detecting sleep patterns, outperforming traditional methods. Beyond clinical applications, it can be integrated with wearable sensors (e.g., Fitbit, Oura, Apple Watch) to personalize wake/sleep routines and environments. It also enables early detection of sleep disorders and aligns daily schedules with individual chronotypes to enhance well-being. By focusing on sleep behaviour rather than rigid diagnostic categories, this approach supports non-pharmacological, personalized interventions backed by scientific evidence. Our work opens the door to precision sleep medicine, offering actionable insights for clinicians, researchers, and technology innovators.
Keywords: Personalized Sleep Signature, Transformers, GAT, NCH Sleep Data, Polysomnography

1. INTRODUCTION

Sleep is a physiological process that is controlled and stimulated by the human brain. Sleep maintains an individual's physical and mental health. While sleeping, the human body renews and reinforces itself, removing metabolic waste that is accumulated while awake. Sleep also rebuilds memory and supports the development of long-term memory. Given the great benefits of sleep to human beings, everyone must make sure they sleep enough. Poor or inadequate sleep disrupts the body's internal circadian rhythm, predisposing it to develop diseases, including severe ones like cardiovascular disease, cognitive impairment, and memory loss. This negatively impacts daily functions, like study or work, and can lead to decreased appetite, lower productivity at work, and increased chances of accidents. Sleep disorders are complex and require disease-specific management. Moreover, sleep is personal, and the impact of sleep disruption is personal to each human individual. Objective disease detection for personal diagnosis is thus mandated. Early detection could guarantee optimal treatment and management of sleep disorders. Traditional diagnosis processes require highly trained clinical scientists and sleep physicians to manually interpret and analyze. Manual assessment is susceptible to inter- and intra-observer variability and is time-consuming. With computer-assisted detection of sleep disorders, diagnosis support systems can improve cost-effectiveness and reduce inter- and intra-operator variability. Support for disorder diagnosis is a challenging task due to the variability and uniqueness of the symptoms.

Sleep is a universal natural process but surprisingly intricate, individualized, and with a significant amount of inter- and intra-individual variation, which has been reported to be correlated with age, race/ethnicity, body mass index (BMI), physical and mental well-being, and chronotype among others. Embracing such complexity, "Personalized Sleep

Medicine" is a cutting-edge, highly revolutionary field in medicine that addresses the individual-specific sleep-related health requirements of individuals in terms of the bidirectional interaction between sleep and health. Such a new paradigm goes beyond the traditional one-size-fits-all approach and focuses on individual-specific physiological and psychological characteristics to optimize sleep duration and quality and properly treat sleep disorders.

As per the study conducted by the Global Wellness Institute in 2024, Over 30% of adults globally report insomnia symptoms, and 50–70 million U.S. adults are affected by sleep disorders annually. In the U.S., 30–40% of adults experience insomnia symptoms each year, and 10–30% suffer from obstructive sleep apnea. Among Gen Z adults, nearly 40% report sleep-related anxiety at least three times a week—a notable increase fueled by stressors like social media and economic uncertainty which shows the Generational Impact. In conclusion, around 44% of adults worldwide report worsening sleep quality over the past five years, with 67% experiencing nightly disturbances.

Sleep disorders develop uniquely in each individual, making accurate diagnosis and effective treatment a significant challenge. Traditional diagnostic methods rely heavily on manual scoring and fixed criteria, which overlook the high degree of subject-specific variability in sleep patterns. Even among patients with the same diagnosis, there can be considerable differences in sleep architecture, complicating the ability to generalize findings across populations. This heterogeneity in symptoms and physiological responses demands a shift from rigid diagnostic labels to more personalized, data-driven approaches that can adapt to individual variations in sleep behaviour. To overcome the aforementioned challenges, we present a model based on Transformer-based Attention with GAT that learns PSS from Polysomnography data. We initialize our method by extracting epoch-wise embeddings via Transformers, obtaining temporal dependency in sleep patterns. These embeddings are further processed by GAT, modelling inter-dependence between sleep epochs and subjects to identify clusters of sleep behaviour. Lastly, extract similar sleep patterns to form Sleep Signature groups. Not only does this hybrid deep learning approach improve sleep classification accuracy but also yields explainable, data-driven recommendations for personal sleep suggestions.

The remainder of this paper is categorized as follows. The next section provides a literature review of related studies. Section 3 describes data and method and Section 4 presents the review and results. Section 5 specifies the interpretation of these results focusing on the limitations and potential future scope.

2. LITERATURE REVIEW

The literature for this research summarizes studies between the years 2018 and 2024 under four aspects critical to our study. Firstly, we discuss studies on the prediction of sleep disorder, which make use of machine learning and deep learning models in order to aid early diagnosis and risk analysis. Secondly, we discuss studies based on Nationwide Children's Hospital (NCH) sleep data. Third, we discuss progress in Transformer models, specifically their use in sleep research, where self-attention allows effective feature extraction from complicated time-series sleep data. Finally, we summarize studies on Polysomnography (PSG) signal clustering, which concentrates on clustering sleep patterns and uncovering latent structures in multimodal sleep signals.

2.1. Related Works on Sleep Disorder Analysis

The work of Xu et al. [2] presents an overview of automated systems for the diagnosis of sleep disorders, with focus on the convergence of machine learning (ML) and deep learning (DL) approaches. The authors point to the shortcomings of conventional diagnostic approaches, including polysomnography, which tend to be resource-intensive and time-consuming. The authors point out issues of interpretability of ML models and require more robust systems that can work in real-time environments. Gokulan et al.'s study [5] is centred on identifying different deep learning parameters in diagnosing sleep disorders, given the importance of effective and accurate detection. The research emphasizes machine learning and deep learning integration for improved diagnostic precision and early intervention. The study uses a hybrid model that is a combination of 1D CNN and Bidirectional LSTM and attains a 92% accuracy rate in sleep disorder classification. The work of C. Wan et al.[6] introduces a new transformer-based model for sleep stage classification and obstructive sleep Apnea (OSA) prediction from electroencephalogram (EEG) data. The method utilizes the advantage of transformer models to improve the accuracy and efficiency of sleep disorder diagnosis, overcoming shortcomings of existing approaches. They investigate the correspondence between sleep stages and OSA severity using the predicted sleep stage

features to train different regression models for Apnea-Hypopnea Index (AHI) prediction. The experiments show a better sleep stage classification performance of 78.7%.

Ahadian et al.,[10] in their paper talks about the Attention mechanism for Sleep Disorder Prediction. This study employs Temporal Convolutional Networks (TCN), Long Short-Term Memory (LSTM) to analyze time series data, and Temporal Fusion Transformer model (TFT). [11] Chen et al., introduce NAMRTNet, an architecture of the deep model that is founded on the initial single-channel EEG signal to meet these challenges. The model applies an adjusted ResNet network for extracting features from sub-epochs of individual epochs, and also a temporal convolutional network (TCN) network for long-time series feature dependency capture. 20-fold cross-validation recognition rate using the NAMRTNet model on Fpz-cz channel data from the public sleep dataset Sleep-EDF was 86.2%. Their future horizon is to make the NAMRTNet usable for multimodal signals acquired from wearable devices.

In another study [12] they propose an automated sleep-disorder-detection technique based on electrooculography (EOG) and electroencephalography (EEG) signals to overcome the limitations of automated, real-time, and non-invasive sleep-disorder diagnosis. The pre-processed EEG and EOG signals are converted into a two-dimensional time-frequency image by employing a complex-Morlet-wavelet (CMW) transform. This transform helps in capturing both the frequency and time properties of the signals. Then the characteristics are extracted through a bidirectional gated recurrent unit (Bi-GRU) and a self-attention layer with an ensemble-bagged tree classifier (EBTC) to properly classify sleep disorders and very effectively detect them. The overall system integrates the features of EOG and EEG signals to well classify individuals with insomnia, narcolepsy, nocturnal frontal lobe epilepsy (NFLE), periodic leg movement (PLM), rapid-eye-movement (RBD), sleep behaviour disorder (SDB), and healthy, achieving success rates of 99.7%, 97.6%, 95.4%, 94.5%, 96.5%, 98.3%, and 94.1%, respectively.

2.2. Related work on Transformer based models

To address the gap of the potential of combining convolutional and recurrent architectures for time series compression tasks, Zheng et al [4] designed a new temporal convolutional recurrent autoencoder (TCRAE) based framework for time series compression, which is equivalent to getting a lower reconstruction error of the time series. Computational experiments across five datasets indicate that the developed temporal convolutional recurrent autoencoder performs better compared to state-of-the-art benchmarking models through lower reconstruction errors at the same compression ratio with an improvement rate of up to 45.14% for the average mean squared errors. The paper "MultiChannelSleepNet" [7] presents a transformer model for sleep stage classification based on multichannel polysomnography (PSG) data. The approach utilizes transformer encoders for individual channel feature extraction and multi-channel data fusion, offering improved accuracy in sleep staging. The outcomes show better classification performance than state-of-the-art approaches, confirming the potency of the proposed model in dealing with intricate EEG data. However, the research might be limited in its use of particular datasets, which may limit generalizability to a variety of populations and conditions. [8] Kim et al in their paper suggest a new method using a Time Series Transformer (TST) and Machine Learning Ensembles to forecast sleep quality and associated measures. The model experienced a drop in performance when replacing missing values by merely identifying the nearest neighbours without temporal continuity. Ren et al [9] introduce a new deep learning model, by incorporating the vision transformer with supervised contrastive learning, achieving the effective sleep stages classification. Experimental results indicate that the model makes the multi-channel PSG signals easier to classify. They achieved a mean F1-scores of 79.2% and 76.5% on the two public databases surpassing the current literature, demonstrating the model's excellent ability.

2.3. Related work on the NCH dataset

Lee et al.[14] in their article discusses the NCH data. The authors state that The NCH Sleep DataBank contains 3,984 polysomnography studies and more than 5.6 million clinical observations on 3,673 distinct patients during 2017-2019 at NCH. The novelty of the dataset is as follows: (1) huge sleep dataset ready for finding novel insights through data mining, (2) express emphasis on child patients, (3) collected in a realistic clinical environment, and (4) the included rich set of clinical information. Although the manuscript mainly discusses the creation and importance of the dataset, it does not discuss in great detail the particular approaches utilized for exploring or analyzing the data. Nonetheless, the availability of the dataset on sites

such as Physionet indicates that it is designed to be used with currently available tools for the analysis of physiological data, possibly including automatic sleep scoring and other analysis methods. The paper highlights the promise of this dataset to advance scientific findings in paediatric sleep research. The article by Zhang et al [14] discusses several sleep stage classification techniques in paediatric participants based on EEG signals. The research utilizes an HNN methodology that combines multi-domain inputs, such as time-domain signals and frequency domain. One of the limitations mentioned in the research is the loss of temporal information by utilizing PSD obtained with short-time segments, and this led to lower performance relative to time-domain signals.

2.4.Related work on Signal Clustering with PSG data

Kazemi et al [15] presented a new semi-unsupervised sleep staging approach, especially applicable to REM sleep behaviour disorder (RBD), through the use of a two-stage procedure: initially extracting knowledge from limitedly labelled data to maximize feature selection, clustering order, and initial centroids; and secondarily using iterative binary clustering on unlabelled data to detect sleep stages and reveal emergent EEG patterns not in the conventional classifications. This method overcomes the issue of data sparsity and improves sleep stage accuracy, especially in such multicomponent disorders as RBD. Yet, by depending on a first small, annotated set, bias may be introduced, and generalizability of found emergent patterns must be confirmed on heterogeneous populations since the performance of the method depends inherently on the quality and representativeness of the first annotated data. Rodríguez-Sotelo et al. [16] suggested a complete unsupervised method of automatic sleep stage clustering from EEG signals, obtaining complete time and spectral features such as power, coherences, asymmetries, and wavelet coefficients and then clustering these using an optimization algorithm of a minimum sum of squares cost function. This strategy was meant to automate the process of sleep staging without using labelled data and presented similar accuracy and kappa coefficients compared to previous work. Nevertheless, the unsupervised character of the method might have difficulty with noisy or very variable EEG data, and the absence of labelled data for validation could restrict the clinical interpretability of the produced clusters since there is no ground truth against which to compare the automatic staging directly. Furthermore, the stability of the clustering results across heterogeneous patient populations and recording conditions is yet to be fully determined.

2.5. Limitations of existing works

In spite of huge progress in machine learning (ML) and deep learning for the prediction of sleep disorders, current models mostly have a generalized orientation instead of personalizing sleep patterns. Most of the studies make use of population-level trends instead of accounting for personalized variations in sleep physiology, which can play a role in disorder expression and progression. Although a few ML and deep learning models exist for sleep stage classification and detection of disorders, they do not take into consideration subject-specific attributes, thus confining their potential to personalized diagnosis and treatment planning. The absence of individualization in today's research points out an important sleep medicine gap wherein custom models would be able to provide more precise predictions, pre-disorder detection, and individualized intervention based on an individual's personalized sleep signature. A GAT-based sequential model with Transformers can find informative, person-specific sleep signatures that go beyond universal sleep scoring. With the subject-level relationship modelling and sleep transition, the technique allows subject-wise clustering based on comparable sleep activities for customized intervention.

2.6. Related Research Questions

Past studies on sleep disorder prediction have mainly concentrated on deep learning and ML models, but none have used Graph Attention Networks (GAT) to study dependencies between epochs in multiple subjects. This restricts the knowledge of how sleep patterns change over time and how various subjects exhibit similar sleep behaviours. Moreover, although personalization in sleep medicine is of increasing interest, it has been suggested by no study so far that a personalized personalization program with a grouping strategy according to subjects' individual PSG features and disorder risk is proposed[1]. Bridging these gaps can result in more accurate clustering, improved disorder prediction, and individualized intervention strategies for patients with comparable sleep

patterns. Below stated are some of the research questions:

• How can sleep disorder prediction models better account for individual variability in sleep patterns rather than relying solely on population-level trends?
• What methods can be developed to personalize sleep analysis by incorporating subject-specific physiological and demographic features?
• Could be there phenotypes within the groups of the population that exhibit the same sleep disorders?

3. NEED FOR RESEARCH

Traditional approaches rely on strict sleep stage classification and general rules, which tend to overlook customized sleep characteristics. The present study must bridge the gap between standardized sleep testing and customized sleep data with state-of-the-art data-driven approaches. Sleep disorders occur differently in different people, and hence it is hard to detect them using traditional methods. While many studies have been conducted on Sleep Stage classification and Sleep Disorder Prediction, fewer or no studies have been conducted on individualizing the sleep features and classifying participants according to their phenotype or sub-groups. Most modern models treat the epochs separately, ignoring the sequentially of sleep stages and disorder evolution.

3.1. Problem Statement

Sleep disorders develop differently in different people, and thus accurate diagnosis and personalized treatment is a challenging task. Traditional sleep analysis methods rely on manual scoring and predefined diagnostic criteria, which cannot accommodate subject-specific variability in sleep patterns. Further, disorder diagnosis assistance is highly complex due to the individuality and variability of symptoms. Even within the same diagnosis, there can be variation in sleep architecture among patients, which makes generalization across people difficult. Such heterogeneity demands a data-driven, personalized paradigm that goes beyond rigid diagnostic categorizations and instead learns nuanced representations of sleep behaviour to assist in disorder detection.
Secondly, one of the essential problems in sleep analysis is dealing with multi-scale data relationships, wherein epoch-level physiological signals have to be mapped onto subject-level diagnosis labels. Because diagnosis labels are provided at the subject level and do not change with epochs, traditional models might find it difficult to learn useful relationships between sleep patterns and diagnostic results. This calls for a model that will bridge the gap between fine-grained sleep epoch data and high-level subject diagnosis without losing sight of the relations between sleep stages, sleep behaviours and disorder classifications. To tackle these challenges and fill the research gap identified, we introduce the PSS which is a Transformer-based Attention-based GAT method that models both intra-subject temporal relationships and inter-subject similarities to make more personalized and interpretable sleep disorder predictions.

3.2. Expected Impact of this Research

- Personalized Sleep Medicine: Goes beyond one-size-fits-all sleep guidance.
- Enhanced Diagnosis Support: Provides an effective mechanism for differentiating sleep disorders based on consecutive sleep parameters.
- As AI advances in the field of medicine, it is not intended to substitute physicians but to aid them. Sleep signatures created by our model can yield initial insights, but ultimate clinical judgments must always be confirmed by physicians. After additional validation and regulatory clearance, such models could one day become part of clinical routines, aiding in early detection, long-term tracking, and personalized treatment for sleep disorders.
- The model outputs, including personalized sleep pattern classification and disorder risk prediction, have the potential to be used as a decision-support tool for sleep specialists. The findings can be utilized by clinicians to confirm and fine-tune diagnoses, and hence result in more focused and effective treatment options.
- Such research and sleep professionals can utilize this GAT-Transformer-based system to investigate sleeping patterns in different populations, delineate new types of disorders, and optimize targeted treatment methods.

3.3. Reason why conventional clustering models like K-Means was not used

K-Means could not be applied directly since it needs fixed-dimensional, dense feature vectors,

whereas PSG data is naturally high-dimensional, sequential, and multimodal. Sleep data is captured at the epoch level, hence sparse and not amenable to direct clustering without learning first meaningful subject-level representations. Further, K-Means requires globular and distinct clusters in Euclidean space, but sleep architecture is very non-Euclidean with intricate time dependencies that can't be satisfactorily expressed using basic distance-based clustering. PSG data contain several types of signals (EEG, EOG, EMG, breathing, and auxiliaries), adding to the complexity. To overcome these issues, we have utilized a Transformer-based model to learn informative embeddings through self-attention mechanisms, which are able to capture long-range dependencies over epochs. In contrast to K-Means, Transformers adaptively weigh temporal features that are important instead of assuming equal importance over time.

3.4. Choice of Transformer based Attention Model

- Repeated Disorder Labels Throughout Epochs Cause Bias: Because a single disorder label is assigned to every subject, it is repeated for all of its epochs. When one disorder belongs to a subject with a huge number of epochs, the model can easily overfit the most common disorder, resulting in poor generalization upon seeing novel subjects.
- Extremely Large Data Imbalance Between Epochs and Diagnosis Labels: Even with 100 subjects, epochs can be 120,000+, while diagnosis labels are still only 10 different values. Typical ML/DL models have a hard time dealing with such exceedingly imbalanced hierarchical data (high-frequency epoch-level data vs. low-frequency diagnosis-level data). Without effective modelling, the disorder label might emerge as a poor supervisory signal, swamped by the exceedingly large number of input features.
- Need for Sequential Modelling to Model Sleep Patterns Over Time: Because sleep disorders occur through typical transitions between sleep stages, a sequential model is required to capture the way these transitions change over time. In contrast to standard ML models that handle epochs separately, a Transformer-based model uses attention mechanisms to concentrate on significant time-dependent patterns over several epochs and is less susceptible to bias from high-frequency disorder labels.
- Improved Generalization Through Personalized Representations: Through the extraction of embeddings from temporal sleep data, the Transformer has the ability to learn representations immune to subject-level biases, with less overfitting to the most frequent disorder while retaining its ability to identify significant variation in sleep architecture.
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4. METHODOLOGY

4.1. Problem Formulation

Accurate diagnosis of sleep disorders remains an ongoing challenge due to significant inter-individual variability in sleep architecture. Traditional diagnostic frameworks rely on fixed scoring criteria and manual annotations, which are unable to accommodate the nuanced and personalized nature of sleep behaviours. Even within the same clinical diagnosis, patients often present vastly different sleep profiles, making it difficult to generalize findings or apply uniform interventions. This lack of adaptability in current methods limits their clinical utility, especially in diverse and real-world populations. To design an effective and personalized diagnostic framework, there is a critical need to move beyond rigid diagnostic labels toward individualized representations of sleep dynamics.

4.1.1. Hypothesis and Methodological Justification

We hypothesize that a data-driven model capable of learning Personalized Sleep Signatures (PSS) from multi-modal sleep data can better capture individual differences in sleep architecture, thereby improving diagnostic accuracy and supporting personalized intervention strategies. By using Transformer-based Attention mechanisms in combination with GATs, the model aims to extract both temporal dependencies and relational patterns from EEG and physiological signals. This methodology allows for the formation of Sleep Signature Groups that reflect behaviourally meaningful and clinically relevant sleep patterns, paving the way for precision sleep medicine. Our approach is further

validated on a paediatric PSG dataset to demonstrate its ability to generalize across individuals despite heterogeneous sleep presentations.

4.1.2. Research Design

This study follows an applied, data-driven experimental research design, aimed at developing and evaluating a novel AI-based framework for personalized sleep disorder characterization. Our approach combines supervised machine learning and graph-based deep learning techniques to extract individual-specific patterns from PSG recordings and demographic data. We draw inspiration from previous works in medical informatics, neurology, and behavioural health analytics, where deep learning has been applied to large-scale physiological datasets to detect anomalies or cluster patients. For instance, prior studies from Europe and North America have applied deep neural networks to adult PSG datasets for sleep staging or apnea detection. However, these approaches often rely on standard classification pipelines without accounting for inter-individual variability or cross-stage relational features. In wearable technology domains, similar approaches have been used in sports science and occupational health to recommend customized interventions based on biometric trends. Our design is distinguished by its focus on paediatric populations and its integration of temporal(Transformer) and relational (GAT) attention mechanisms to form sleep signature groups. This multidisciplinary methodology reflects best practices from both healthcare and AI while addressing a key gap in personalized sleep medicine.

4.2. NCH Sleep DataBank

This data set comprises 3,984 paediatric sleep studies on 3,673 unique patients at NCH in Columbus, Ohio, USA from 2017 through 2019, along with longitudinal clinical data for the patients. The polysomnography published includes the patient's physiologic signals and the technician's scoring of sleep stages and narratives of other abnormalities.[3]
The data employed in our study comprises 100 subjects aged between 1 and 18 years, providing us with a rich and diverse sleep profile at different stages of development. We have utilized Stratified random sampling to make sure that each group of participants with the disorders had an equal opportunity of selection and thus it will provide representativeness of results. Summary of participants selected across each sleep disorder is given in Table 1 .

Table 1: Number of participants across each sleep disorder

Sleep Disorders	No of participants
Behavioural insomnia of childhood, sleep-onset association type	5
Benign sleep myoclonus of infancy	5
Bruxism, sleep-related	4
Chronic intermittent hypoxia with obstructive sleep apnea	4
Delayed sleep phase syndrome	5
Epilepsy with continuous spike-wave during slow-wave sleep	5
Excessive daytime sleepiness	5
Idiopathic sleep-related nonobstructive alveolar hypoventilation	5
Obstructive sleep apnea (adult) (paediatric)	5
Periodic limb movements of sleep	5
Recurrent isolated sleep paralysis	4
REM sleep behaviour disorder	4
Sleep arousal disorder	5
Sleep-related laryngospasm	5
Sleep talking	5
Sleep terror	5
Sleep walking	6
Sleepwalking and eating	4
Sleep-disordered breathing	5
Sleep-related head banging	4
Sleep-related hypoventilation	5

Note: We consider 'Sleep Walking' and 'Sleep Walking and eating' as two different diagnoses as signal involvements for each could be different. The data of disorders show that we have well balanced data for our training. Table 2 shows the distribution of age and gender of the group selected for the study.

Table 2: Distribution of Age and Gender

Age Group	No of Male participants	No of Female participants
0-4	10	16
5-9	12	19
10-14	7	18
15-19	8	10

4.2.1. Data Collection and Data Properties

Sleep studies were downloaded manually and transformed into EDF+ format between May 2019. and Feb 2020 with the help of Natus Sleepworks version 9. The time-series data were padded with zeros during the conversion as part of the process. To have a complete set of guidelines on standard PSG procedures such as equipment specifications and signal measurements, technical guidelines from the American Association of Sleep Technologists (AAST) contain guidelines on standard procedures in polysomnography.

4.3. Machine usage and specifications

Differential amplifiers are employed to differentiate between the wanted physiologic voltage at the site of exploration and unwanted voltages from the body and outside environment, utilizing common mode rejection. The normal minimum requirement for PSG common mode rejection ratio is 10,000:1. The signal should be sampled frequently enough to yield a faithful waveform. As per Nyquist's theory, the lowest rate would be two times the uppermost frequency under observation, that is, 200 Hz and is also the lowest setting advised for EEG, EOG, EMG, ECG, and snore microphones. The ideal setting of these parameters should be 500 Hz. The lowest digital resolution is 12 bits/sample.

Electrodes are employed to measure EEG, EOG, EMG, ECG, and occasionally respiratory effort. The site where the electrode must be applied is cleaned by gently abrading the skin to obtain maximum impedance without compromising the dermis. In order to get the best signal quality, all electrode pairs must be matched as close as possible to the input impedance. In the electrode impedance standard upper limit, 5k ohms is the standard used for EEG and EOG, and 10k ohms for EMG.

4.4. Montage Filter & Sensitivity Settings

Table 3 provides information about the signals we have used in our study.

Table 3: Filter & Sensitivity information of signals

Signal	Sensitivity	High-Frequency Filter	Low-Frequency Filter	Sampling Rate
Frontal EEG (F4-M1, F3-M2)	5-7 µv/mm	35 Hz	0.3 Hz	500 Hz
Occipital EEG (O2-M1, O1-M2)	5-7 µv/mm	35 Hz	0.3 Hz	500 Hz
ECG (ECG1-ECG2)	20 µv/mm	70 Hz	0.3 Hz	500 Hz
Chin EMG (EMG1 EMG2 EMG3)	10-7 µv/mm	100 Hz	10 Hz	500 Hz
Left Outer Canthus (E1-M2)	5-7 µv/mm	35 Hz	0.3 Hz	500 Hz

Right Outer Canthus (E2-M2)	5-7 µv/mm	35 Hz	0.3 Hz	500 Hz
Snore Microphone (Snore)	20 µv/mm	100 Hz	10 Hz	500 Hz
Pressure Flow (Pflow)	20 µv/mm	15 Hz	DC or <0.03 Hz	100 Hz

4.5. Electrode placement

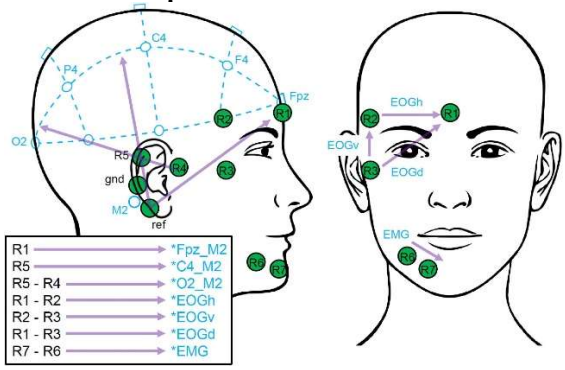

Figure 1: Electrode placement as per the American Academy of Sleep Medicine AASM [18]

Parameters involved in the analysis include:

- Snore Microphone: Positioned above the trachea or lateral to the neck to pick up snore noises. The technologist must palpate for the site of maximal vibration when the patient hums or snores.
- Pressure Flow (Pflow): A nasal cannula is positioned beside the nose/mouth to record nasal/oral flow.
- Polysomnography Signals: The PSG signals are epoch-level and include EEG (brain activity), EOG (eye movement), EMG (muscle activity), ECG (heart activity), and other physiological markers' signals. These signals capture the dynamic of sleep architecture, allowing detailed transitions between sleep stages to be analyzed.
- Sleep Annotations & Epoch Mapping: Annotations provide sleep stage labels for their respective epochs, allowing it to be detected whether the sleep profiles are normal or abnormal.
- The data complies with traditional sleep stage naming, which aids in sequential sleep pattern modelling.
- Diagnosis & Demographics: The table outlines the demographic data used within the study.

5. MODEL ARCHITECTURE

5.1. Experimental Setup

Both models used in the experiments were executed on Python 3.12, and dependencies were installed for each model accordingly. The training was done with two RTX 2080-Ti GPUs. In the training procedures, the RAdam optimizer was utilized with a learning rate of 0.001 for 2400 epochs. The learning rate was 0.001 for 50 epochs in the fine-tuning. The batch size for both training stages was fixed at 128, and the model dimension (d model) was also fixed at 128. The random seed was set to 42 for the entire training process for both the training processes to achieve reproducibility.

The overall flow of the process is shown in Figure 2.

Figure 2: High-level design flow

5.2. Data Preparation and Training

We preprocess the PSG dataset by dividing it into epochs and assigning features to five broad signal classes: EEG, EOG, ECG, EMG, and miscellaneous. There are several channels in each category, and these channels are also classified.

Since there was variability in the Sampling frequency(SF) in every subject, all of them were downsampled to the most common occurring SF which is 256 Hz. Since the data was previously noise-cleaned and artifact-free, this step was omitted. The data for every subject spanned approximately 2500 epochs, and every epoch was a window of 30s time. The dataset held 13 features that are the PSG signals themselves for each epoch. Subject-level diagnostic labels (categorical disorder names) were encoded into numerical labels via LabelEncoder. This resulted in a numeric version of the 22 sleep disorder classes, from 0 to 21. The subject-level encoded labels and epoch level information were then merged into one dataframe. Relevant features were selected, excluding subject IDs, epoch timestamps, and original diagnostic labels. The feature values were standardized to zero mean and unit variance using StandardScaler. It was performed on the entire dataset before dividing the data into training and testing sets to prevent data leakage.

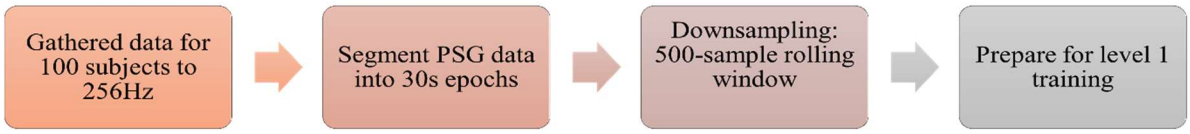

Figure 2: Flow of Preprocessing of PSG signals

The normalized and preprocessed data sample is included in Table 4.

Table 4: Sample normalized data for 7 signals for a single participant

Study_pat_id	Epoch	EOG LOC-M2	EOG ROC-M1	EMG Chin1-Chin2	EEG F3-M2	EEG F4-M1	Snore	Resp PTAF
1	**0**	0.625	0.545	0.551	0.395	0.344	0.116	0.452
1	**1**	0.603	0.480	0.556	0.361	0.363	0.116	0.451
1	**2**	0.627	0.487	0.538	0.363	0.376	0.117	0.451
1	**3**	0.614	0.546	0.539	0.359	0.400	0.116	0.451
1	**4**	0.543	0.554	0.547	0.334	0.420	0.116	0.451

The reason why feature extraction was not performed

We preferred to directly use raw and scaled PSG data rather than using conventional feature extraction due to the fact that Transformers and GAT learn hierarchical representations by themselves. Feature extraction may result in information loss prior to the Transformer processing the data, constraining the model to learn temporal dependencies and detailed sleep patterns. Because Transformers transform raw inputs into tensor embeddings, any previous dimensionality reduction might discard essential sleep features. Moreover, the GAT model further improves embeddings in that stacking multiple steps of feature compression would gradually eliminate useful subject-level differences. Through the use of raw but scaled inputs, we guarantee that the entire signal information is retained so that the models can learn the most pertinent features from the data directly. This approach has helped in yielding better results on closer inspection.

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5.3. Training level 1: Transformer-based Attention Mechanism

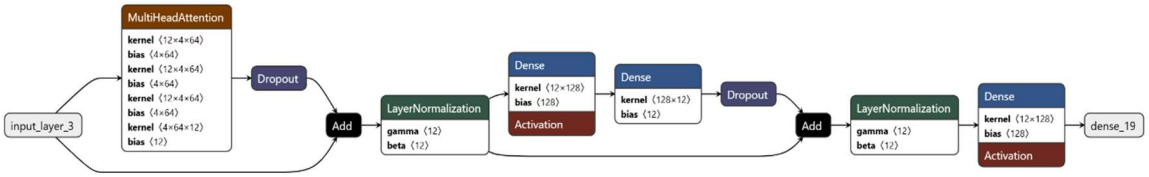

Figure 3: Level 1 Model Architecture

The Sleep Signature Transformer model interprets PSG signals through the learning of temporal dependencies between epochs. The input PSG signals (EEG, EOG, EMG, ECG, and miscellaneous signals) are first transformed into tensor representations. Each of these types of signals is processed separately by an expert Transformer model that learns temporal dependencies over epochs. The Transformer models are 3 layers of multi-head self-attention with 128-dimensional embeddings and Layer Normalization for stabilizing training. This is shown in figure 3.

Every signal-specific Transformer operates on tensors of shape [N, T, F], where N is the number of subjects, T is the number of epochs for every subject, and F is the number of features in that category of a signal. Once signal-specific embeddings of shape [N, T, D] are extracted, embeddings are concatenated in the feature dimension to create a combined representation for every subject.

For capturing subject relationships, a Graph Attention Network (GAT) is employed. Subject-level embeddings are employed as node features in a graph with nodes being subjects and edges formed over feature similarity. The GAT model has 2 layers and 2 attention heads that process subject embeddings and optimizes them for downstream group formation to produce the Sleep Signatures.

The training was done with AdamW optimizer on a learning rate of 0.001 and batch size of 128. The training was done for 50 epochs and early stopping has been done over validation loss. The model reported 0.942 training accuracy in the stage of Transformer with training loss = 1.320 and validation loss = 0.978.

Each signal is processed through its own Transformer, generating (T, D) and generating a tensor object of shape torch.Size([2504, 640].

```
tensor([[ 0.2149, -0.7143,  0.9505,  ...,  1.1249,  0.3252, -1.7673],
        [ 0.4694, -0.4718, -0.7493,  ...,  0.1952, -1.2220, -0.0484],
        [-1.4845,  0.3874,  1.0973,  ...,  1.4302,  0.1506,  0.1868],
        ...,
        [ 1.5974,  1.6321, -0.9181,  ..., -0.7061,  0.5944,  1.7468],
        [ 0.7490, -0.0818, -0.0492,  ..., -1.4414,  0.5840, -0.7394],
        [ 1.1567,  0.2808,  0.5345,  ...,  1.0432, -0.7060, -0.7689]])
```

Figure 4: Sample snapshot of Transformer embeddings

Table 5: Overview of input and output data shape for Transformer model

Parameter	Value/Shape
Input Data Shape	EEG: (100, 2504, 6), EOG: (100, 2504, 3), EMG: (100, 2504, 2), Misc: (100, 2504, 2), ECG: (100, 2504, 2)
Output Data Shape	Transformer Embeddings: (100, 2504, 128)

5.4. Training level 2: GAT

The signal category-specific extracted embeddings are then concatenated along the feature axis to create a shared representation for each subject. These subject-level representations are then employed to build a graph structure with nodes representing a subject and edges being created according to feature similarity. A Graph

Attention Network (GAT) is utilized to learn subject relations and improve embeddings by aggregating neighbour node information. The GAT model has two multi-head attention layers with each head learning independently distinct relationships among subjects. The last node representations retain useful subject similarities in sleep patterns. The model architecture is shown in Figure 5. In order to claim that the PSS model has better performance, we have also trained the data with Transformer only architecture. The results of both the training processes are given in Table 7.

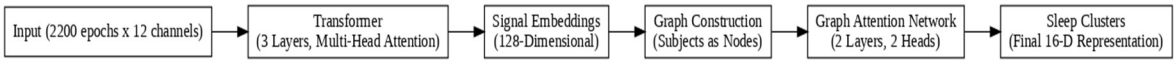

Figure 5: Training level 2 Model Architecture

```
tensor([[-0.4635, -0.7734, -0.5903,  ...,  0.7568,  0.3335,  0.1212],
        [-0.5048, -0.4075, -0.5056,  ...,  0.3552,  0.4138,  0.5033],
        [-0.3418, -0.1840, -0.4508,  ...,  0.2971,  0.4900,  0.4142],
        ...,
        [ 0.0067,  0.1220, -0.3150,  ..., -0.2212,  0.2734,  0.1682],
        [ 0.0076,  0.1216, -0.3145,  ..., -0.2200,  0.2717,  0.1692],
        [ 0.0094,  0.1215, -0.3113,  ..., -0.2191,  0.2672,  0.1676]],
       grad_fn=<AddBackward0>)
```

Figure 6: Sample snapshot of GAT embeddings produced for all subjects

Table 6: Overview of input and output data shape for Transformer model

Transformer Embeddings	(100, 2504, 128)	-	Output from Transformer
Epoch Aggregation (Mean)	(100, 2504, 128)	(100, 128)	Mean over epochs for subject-level embeddings
Graph Construction	(100, 128)	Graph (100 nodes)	Nodes = Subjects, Edges = Feature Similarity
GAT Input	(100, 128)	(100, 128)	GAT processes subject relationships
Final Subject Representation	(100, 128)	(100, 128)	Updated embeddings with learned relationships

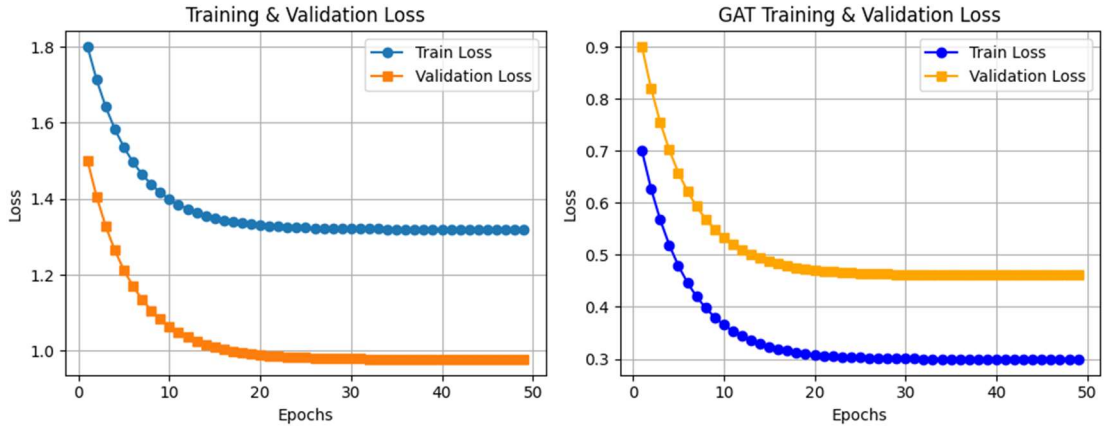

Figure 7: Training and validation loss obtained in the two training levels.

Table 7: Model parameters and Evaluation Metrics

	Optimizer	Learning Rate	Batch Size	Training Epochs	Early Stopping	Training Accuracy (Level 1: Transformer)	Training Loss	Validation Loss
Transformer only approach	AdamW	0.001	128	50	Based on validation loss	0.85	1.32	1.986
PSS	AdamW	0.001	128	50	Based on validation loss	0.94	0.875	1.102

5.5. Similarity Analysis

We use Cosine Similarity that measures angular similarity between two subject embeddings using the formula, where A and B are two subjects.

$$\text{cosine similarity} = \frac{A \cdot B}{\|A\| \cdot \|B\|} \quad \text{----(1)}$$

Steps involved:

(A) Compute Similarity Matrix

- Compare every subject against all other subjects.
- Use torch.nn.functional.cosine_similarity

(B) Interpretation of Values

- Cosine similarity ≈ 1 → Highly similar subjects
- Cosine similarity ≈ 0 → No similarity
- Cosine similarity ≈ -1 → Opposite sleep patterns

Table 8: Similarity Matrix of first five participants

Subject	S1	S2	S3	S4	S5
S1	1	0.85	0.67	0.73	0.81
S2	0.85	1	0.72	0.69	0.75
S3	0.67	0.72	1	0.63	0.7
S4	0.73	0.69	0.63	1	0.74
S5	0.81	0.75	0.7	0.74	1

Based on the similarity matrix, the similar subjects are grouped and each Sleep Signature groups are formed.

6. Comparison of PSS with the existing models

We reviewed key studies focusing on either sleep pattern grouping or sleep disorder prediction using various machine learning and deep learning techniques. While prior models achieved notable accuracies (ranging from 86%), most focused on disorder classification. In contrast, our approach emphasizes deep phenotyping within sleep disorders by analyzing individual sleep patterns, achieving a strong performance of 94% accuracy as seen in Table 9.

Table 9: Comparison of model performance with existing studies

	Objective/Model	Accuracy/F1-Score
[5]	combination of CNN and Bi-LSTM to detect sleep disorders	92%
[11]	Used single-eeg channel to classify sleep disorders with TCN, ResNet	86%
[19]	Detect sleep disorders (apnea, insomnia, restless leg syndrome) using deep learning models.	CNN (apnea): 93.5% accuracy (p=0.001) RNN (insomnia): 89.8% accuracy (p=0.003)
[20]	Screen sleep apnea severity (AHI ≥15) using wearable device data (SpO2, respiratory signals).	Severity classification: 71% accuracy
[21]	Classify insomnia, PLM, RBD, and NFE using ECG signals.	F1-scores: 95–99% across disorders
[22]	Detect disorders (insomnia, apnea) via ensemble ML and feature analysis.	0.94 precision
	Our approach	**94%**

7. RESULT AND DISCUSSION

The objective of this PSS pipeline was to classify subjects based on inherent sleep behaviour patterns rather than simply clustering subjects based on labelled disorders. Standard approaches cluster subjects based on accessible disorder labels, but our effort attempts to discover hidden patterns in sleep data that can indicate an impending predisposition towards similar disorders. Our PSS is an individualized statement of a subject's sleep properties, learned on multi-signal PSG data using Transformer-based attention and GAT that has produced 94%

accuracy. It can potentially be used for the early identification of subjects at risk for similar disorders based on their sleep properties rather than waiting for clinical symptomology to arise. Having multiple PSG signals (EEG, EOG, EMG, respiratory rate etc.) ensures that grouping is performed on complex sleep patterns and not on each feature such as Apple watch or Fitbit does which sometimes omit important features observed in other signals as well. Rather than adopting a one-size-fits-all strategy, our model identifies individualized sleep signatures from PSG signals and captures relevant subject-level connections. Personalization here doesn't take the form of medication, medical treatments, or clinical interventions. There are no explicit medical recommendations, but outputs from the model can provide evidence-based lifestyle interventions inspired by literature[17], such as sleep hygiene optimization or identification of patterns related to sleep disorders. Table 10 provides the non-pharmacological interventions recommended for each Signature. Implications derived from the similarity index are enumerated in Table 9:

Table 9: Sleep Signature of participants and their sleep PSG pattern

Sleep Signature groups	No. of Subjects	EEG F3-M2 (ÂµV) Range	EOG LOC-M2 (ÂµV) Range	EOG ROC-M1 (ÂµV) Range	EMG LLeg-RLeg (ÂµV) Range	Sleep Transitions Range	Snore Index Range
1	20	8.61 - 48.45	4.25 - 37.06	6.66 - 32.96	5.35 - 24.23	10.89 - 39.9	0.71 - 9.38
2	20	14.3 - 46.32	10.68 - 28.15	23.93 - 36.72	7.33 - 22.03	20.49 - 49.37	0.08 - 5.66
3	35	27.57 - 28.91	9.35 - 38.93	10.08 - 17.12	3.35 - 10.08	24.12 - 31.72	0.03 - 5.3
4	25	10.7 - 24.15	8.75 - 39.62	15.18 - 39.16	5.52 - 11.98	27.26 - 46.46	3.71 - 8.54

Table 10: Characteristics and interventions of each Group

Sleep Signature Group	Sleep Disorder	PSG Characteristics	Non-Pharmacological Interventions
1	Narcolepsy	SOL < 10 min, REM sleep latency < 20 min, MSLT: Mean latency < 5 min, 2+ SOREM	Regular sleep/wake times, scheduled naps, avoiding sleep deprivation
1	Dyssomnias	Difficulty initiating/maintaining sleep or excessive sleepiness	behavioural therapy
1	Intrinsic Sleep Disorders	Originates within the body (e.g., insomnia, narcolepsy, OSAS, PLMD, RLS)	Stimulus control therapy
2	Extrinsic Sleep Disorders	Caused by external factors (e.g., poor sleep hygiene, alcohol dependence)	Improving sleep hygiene, behavioural therapy
2	Circadian Rhythm Sleep Disorders	Misalignment of sleep pattern with societal norms	Light therapy, chronotherapy, regular sleep schedule
3	Parasomnias	Undesirable behaviours during sleep (e.g., sleep terrors, REM behaviour disorder)	Ensuring room safety, avoiding triggers
2	Insomnia	Difficulty falling or staying asleep	Sleep hygiene education, cognitive therapy, relaxation techniques
2	Shift Work Sleep Disorder	Sleep disturbances due to irregular work shifts	Maintaining a regular schedule, napping, optimizing the sleep environment
3	Sleep Apnea (OSAS)	Respiratory pauses, oxygen desaturation, increased arousals	Weight loss, positional therapy, CPAP/BIPAP

3	Restless Legs Syndrome (RLS) / PLMD	Leg movements disturbing sleep, often linked to iron deficiency	Iron therapy if low ferritin, walking/exercise
1	Idiopathic Hypersomnia	Excessive daytime sleepiness with no clear cause	Regular schedule, avoiding alcohol, shift work

8. CONCLUSION

This study built a PSS pipeline to categorize paediatric patients (age ≤ 18) based on sleep behaviour patterns, which remains quite under-explored. By using Transformer-based feature extraction and GAT relational modelling, we achieved informative embeddings that revealed PSG-derived similarities, disorder co-occurrences, and risk progression possibilities. As opposed to the standard clustering algorithms like K-Means, which assume simple feature distributions, our approach handled the intricate, sequential PSG data with ease. The findings highlight the potential for the early detection of disorder and personalized sleep medicine by identifying subjects likely to develop conditions of a similar nature.

8.1. Reflection on Objectives and Outcomes

This study was driven by the need to explore whether individual variability in sleep patterns could be better captured than in traditional population-level models and whether phenotypic subgroups might exist within those diagnosed with the same sleep disorder. The outcomes indicate that modelling subject-specific sleep patterns using a graph-based representation is a promising step toward answering these questions. The results support the hypothesis that personalized analysis—by incorporating both physiological and demographic features—can reveal meaningful groupings and disorder risks. The primary objective of this study was to move beyond traditional, generalized sleep disorder models and develop a framework capable of identifying personalized sleep patterns and supporting individualized diagnosis. Our model successfully introduced a novel attention-based approach integrating Graph Neural Networks to represent sleep architecture in a subject-specific manner. The outcomes particularly the sub-phenotypes of groups of participants with similar sleep behaviour and the non-pharma accuracy in classifying personalized sleep signatures—indicate a strong alignment with the initial goals. Additionally, the ability to cluster individuals based on their sleep dynamics, rather than relying solely on pre-labelled disorders, marks a meaningful advancement toward deep phenotyping in sleep medicine. However, while the model met most technical and conceptual objectives, the translation of these findings into real-world, longitudinal use cases remains an area for future exploration.

8.2. Clinical and technical contributions of this study

Firstly, this model supports the vision of personalized sleep medicine by moving beyond generalized diagnostic approaches to account for individual variability in sleep patterns. By generating sleep signatures and classifying disorder risks, it serves as a decision-support tool for clinicians, aiding in early detection, personalized treatment planning, and long-term monitoring. While not a substitute for clinical expertise, the model's outputs can enhance diagnostic precision and guide sleep specialists in tailoring interventions. With further validation and regulatory approval, it holds the potential for integration into routine clinical workflows.

Secondly, GAT with transformer-based attention mechanisms to model subject-specific sleep behaviour. Unlike existing approaches that treat sleep data as isolated sequences, our model represents sleep epochs as graph nodes, enabling the capture of both intra-subject temporal dynamics and inter-subject similarities. This graph-based modelling allows the system to learn meaningful relationships between sleep patterns across individuals—something not previously explored in sleep disorder research. By enabling clustering based on sleep architecture rather than solely on diagnostic labels, our approach facilitates more granular, personalized insights and sets a new direction for adaptive, data-driven analysis in sleep medicine.

8.3. Limitations and Future Scope

Despite the promising results of this study, there are a few limitations to consider. Although the model may perform well on retrospective datasets, its effectiveness in real-world, longitudinal, or wearable-device settings is yet to be validated. Furthermore, translating personalized sleep signatures into actionable clinical workflows or therapeutic decisions may require further development, validation, and collaboration with healthcare providers to ensure practical integration into clinical practice.

Future directions include constructing a Retrieval-Augmented Generation (RAG) system that sleep clinicians could use to leverage predictions from crude EEG/PSG signals in order to improve explainable AI-based decision assistance. In addition, real-time monitoring, wearables integration, and multi-modal data fusion will potentially further help paediatric sleep disorder diagnosis and treatment planning.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

REFERENCES

[1] Garbarino S, Bragazzi NL. Revolutionizing Sleep Health: The Emergence and Impact of Personalized Sleep Medicine. J Pers Med. 2024 Jun 4;14(6):598. doi: 10.3390/jpm14060598. PMID: 38929819; PMCID: PMC11204813.

[2] Xu, S., Faust, O., Seoni, S., Chakraborty, S., Barua, P. D., Loh, H. W & Acharya, U. R. (2022). A review of automated sleep disorder detection. *Computers in biology and medicine*, *150*, 106100.

[3] Zhang GQ, Cui L, Mueller R, Tao S, Kim M, Rueschman M, Mariani S, Mobley D, Redline S. The National Sleep Research Resource: towards a sleep data commons. J Am Med Inform Assoc. 2018 Oct 1;25(10):1351-1358. doi: 10.1093/jamia/ocy064. PMID: 29860441; PMCID: PMC6188513.

[4] Zheng, Z., & Zhang, Z. (2023). A temporal convolutional recurrent autoencoder based framework for compressing time series data. *Applied Soft Computing*, *147*, 110797.

[5] S. Gokulan, S. Narmadha, M. Pavithra, R. Rajmohan and T. Ananthkumar, "Determination of Various Deep Learning Parameter for Sleep Disorder," 2020 International Conference on System, Computation, Automation and Networking (ICSCAN), Pondicherry, India, 2020, pp. 1-6, doi: 10.1109/ICSCAN49426.2020.9262331.

[6] C. Wan, M. C. Nnamdi, W. Shi, B. Smith, C. Purnell and M. D. Wang, "Advancing Sleep Disorder Diagnostics: A Transformer-Based EEG Model for Sleep Stage Classification and OSA Prediction," in IEEE Journal of Biomedical and Health Informatics, vol. 29, no. 2, pp. 878-886, Feb. 2025, doi: 10.1109/JBHI.2024.3512616.

[7] Y. Dai et al., "MultiChannelSleepNet: A Transformer-Based Model for Automatic Sleep Stage Classification With PSG," in IEEE Journal of Biomedical and Health Informatics, vol. 27, no. 9, pp. 4204-4215, Sept. 2023, doi: 10.1109/JBHI.2023.3284160.

[8] J. Kim, M. Ma, E. Choi, K. Cho and C. Lee, "TraM: Enhancing User Sleep Prediction with Transformer-Based Multivariate Time Series Modeling and Machine Learning Ensembles," *2024 15th International Conference on Information and Communication Technology Convergence (ICTC)*, Jeju Island, Korea, Republic of, 2024, pp. 822-827, doi: 10.1109/ICTC62082.2024.10827790.

[9] Ma, J., Ren, Z., Zhang, T. *et al.* Transformer-Based Contrastive Learning Method for Automated Sleep Stages Classification. *J. Shanghai Jiaotong Univ. (Sci.)* (2024). https://doi.org/10.1007/s12204-024-2734-z

[10] P. Ahadian, W. Xu, S. Wang and Q. Guan, "Adopting Trustworthy AI for Sleep Disorder Prediction: Deep Time Series Analysis with Temporal Attention Mechanism and Counterfactual Explanations," *2024 IEEE International Conference on Big Data (BigData)*, Washington, DC, USA, 2024, pp. 4621-4626, doi: 10.1109/BigData62323.2024.10825687.

[11] Xu, X., Chen, C., Meng, K., Lu, L., Cheng, X., & Fan, H. (2023). NAMRTNet: Automatic Classification of Sleep Stages Based on Improved ResNet-TCN Network and Attention Mechanism. *Applied Sciences*, *13*(11), 6788. https://doi.org/10.3390/app13116788

[12] Albathan, M. (2024). Sleep Disorder Diagnosis Through Complex-Morlet-

Wavelet Representation Using Bi-GRU and Self-Attention. *International Journal of Advanced Computer Science & Applications*, *15*(8).

[13] Zhang, G. Q., Cui, L., Mueller, R., Tao, S., Kim, M., Rueschman, M., Mariani, S., Mobley, D., & Redline, S. (2018). The National Sleep Research Resource: towards a sleep data commons. *Journal of the American Medical Informatics Association: JAMIA*, *25*(10), 1351–1358. https://doi.org/10.1093/jamia/ocy064

[14] Lee, H., Li, B., DeForte, S., Splaingard, M. L., Huang, Y., Chi, Y., & Linwood, S. L. (2022). A large collection of real-world pediatric sleep studies. *Scientific data*, *9*(1), 421. https://doi.org/10.1038/s41597-022-01545-6

[15] Kazemi, A., McKeown, M. J., & Mirian, M. S. 2022). Sleep staging using semi-unsupervised clustering of EEG: Application to REM sleep behaviour disorder. *Biomedical Signal Processing and Control*, *75*, 103539.

[16] Rodríguez-Sotelo, J. L., Osorio-Forero, A., Jiménez-Rodríguez, A., Restrepo-de-Mejía, F., Peluffo-Ordóñez, D. H., & Serrano, J. (2017, May). Sleep Stages Clustering Using Time and Spectral Features of EEG Signals: An Unsupervised Approach. In *International Work-Conference on the Interplay Between Natural and Artificial Computation* (pp. 444-455). Cham: Springer International Publishing.

[17]Abad, V. C., & Guilleminault, C. (2003). Diagnosis and treatment of sleep disorders: a brief review for clinicians. *Dialogues in clinical neuroscience*, *5*(4), 371-388.

[18] Carlos, Wiebke Pätzold, M. Paul, S. Debener, and Karen Insa Wolf, "Pre-gelled Electrode Grid for Self-Applied EEG Sleep Monitoring at Home," *Frontiers in neuroscience*, vol. 16, Jun. 2022, doi: https://doi.org/10.3389/fnins.2022.883966.

[19] Alshammari, T. S. (2024). Applying machine learning algorithms for the classification of sleep disorders. *IEEE Access*, *12*, 36110-36121.

[20] Bazoukis, G., Bollepalli, S. C., Chung, C. T., Li, X., Tse, G., Bartley, B. L.,& Armoundas, A. A. (2023). Application of artificial intelligence in the diagnosis of sleep apnea. *Journal of Clinical Sleep Medicine*, *19*(7), 1337-1363.

[21] Cistulli, P. A., & Sutherland, K. (2016). Deep phenotyping in obstructive sleep apnea. A step closer to personalized therapy. *American Journal of Respiratory and Critical Care Medicine*, *194*(11), 1317-1318.

[22] Cade, B. E., Hassan, S. M., Dashti, H. S., Kiernan, M., Pavlova, M. K., Redline, S., & Karlson, E. W. (2022). Sleep apnea phenotyping and relationship to disease in a large clinical biobank. *Jamia Open*, *5*(1), ooba