Exploration of LLMs, EEG and behavioral data to measure and support attention and sleep

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Abstract—We explore the application of large language models (LLMs), pre-trained models with massive textual data for detecting and improving these altered states. We investigate the use of LLMs to estimate attention states, sleep stages, and sleep quality and generate sleep improvement suggestions and adaptive guided imagery scripts based on electroencephalogram (EEG) and physical activity data (e.g. waveforms, power spectrogram images, numerical features). Our results show that LLMs can estimate sleep quality based on human textual behavioral features and provide personalized sleep improvement suggestions and guided imagery scripts; however detecting attention, sleep stages, and sleep quality based on EEG and activity data requires further training data and domain-specific knowledge.

 ${\it Index\ Terms} \hbox{--} Large\ Language\ Models,\ LLMs,\ sleep,\ attention,} \\ EEG$

I. INTRODUCTION

Human altered states such as attention and sleep play significant roles in health [1], safety [2], and productivity [3]. By precisely measuring these states, we can design adaptive tools and interfaces that respond effectively to users and help promote their health.

Human attention states have been measured using physiological and behavioral data such as electroencephalogram (EEG) [4], facial expressions [5], and eye tracking [6]. . Measuring human attention states can help design systems that enhance driver alertness, minimize interruptions during focus, or promote relaxation before sleep.

Extensive research has explored computational methods for measuring, evaluating, and improving sleep. For example, many algorithms have been developed to estimate sleep quality and stages using human physiological and behavioral sensor data including EEG and motion [7]. Computational systems have been designed to promote better sleep [8].

Recent advances in natural language processing have leveraged massive textual data to train large language models (LLMs). Some studies have used LLMs for understanding human physiological and behavioral data and designing health applications including EEG abnormality detection and wearable sensor-based sleep quality detection [9] [10].

LLMs hold promise for health applications including human altered state detection and personalized feedback delivery; however, rigorous evaluations have not been conducted, particularly regarding the integration of different human physiological and behavioral data (e.g., waveforms, numerical features,

power spectrogram images) into LLMs for understanding the potential, accuracy, limitations, and reliability of the models.

In this paper, we evaluate LLMs for detecting and supporting human attention and sleep. Our ultimate goal is to create personalized, adaptive systems that enhance individuals' attention and sleep. To achieve this, in this paper, we conduct early explorations by integrating biobehavioral data into LLMs to understand their capabilities. We ask the following two research questions in the paper:

- 1) Can LLMs interpret/sense attentive states, sleep stages, and sleep quality?
- 2) Can LLMs provide personalized and adaptive feedback to help improve sleep?

We investigate the impact of various time scales and different input modalities of EEG, motion, and textual data on LLMs' performance, reasonings, and generated responses for detecting attention states, sleep stages, and sleep quality detection and improving sleep.

II. METHODS

We describe experiments and datasets for 1) user state detection and 2) sleep improvement suggestion generation to address RQ 1 and 2.

A. Experiment 1: user state detection

We conduct three different detection tasks, a) attention detection, b) sleep stage detection, and c) sleep quality detection.

1) Datasets & Data processing: We use the following datasets for our experiments.

Mental Attention State [11]: This dataset contains 25 hours of EEG data collected using 14 ch Emotive. Five participants were engaged in a low-intensity task of controlling a computer-simulated train. Three mental states were observed in this study: focused, unfocused, and drowsy. We merged unfocused and drowsy into an unfocused state. We prepared three different types of information for attention detection (focused vs unfocused/drowsy): a) filtered EEG data (Fig. 1a): Raw EEG signals were processed using a bandpass Butterworth filter (order: 128, 0-40Hz), b) time-frequency spectrograms(Fig. 1b): These were computed using wavelet transform (Daubechies wavelet, every 10 sec) to provide frequency components over time, and c) 11 features: these features include power spectrum density (delta, theta, alpha,

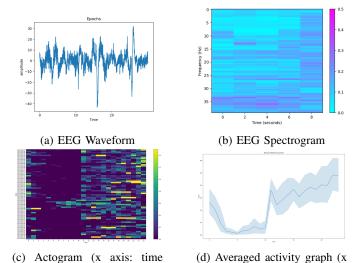


Fig. 1: Image Data Fed into LLMs

axis: time 0am-0am), y-axis:

physical activity levels)

0am-0am), y-axis: dates, z-

axis:physical activity levels)

beta), amplitude, standard deviation, kurtosis, alpha/delta, theta/alpha, delta/theta, the 90th percentile amplitude. We segmented the data into 10-sec intervals, resulting in 919 training samples, 230 validation samples, and 287 test samples.

Sleep EDF expanded [12]: This dataset contains 197 nights of polysomnography data collected from individuals aged 18-101 years. The data include EEG from two channels, Fpz-Cz and Pz-Oz, EOG, EMG, and event markers. Sleep stages are labeled as follows: 0 (Wake), 1 (stage 1), 2 (stage 2), 3 (stages 3 & 4), and 4 (REM sleep). We segmented the data into 30-sec epochs (training set: 152362 epochs, Validation set: 38092 epochs, test set: 500 epochs). We used Fpz-Cz for sleep stage detection. We used the same input types as those used for mental attention states: a) filtered EEG data, b) time-frequency spectrograms, and c) 11 features.

Student Life [13]: This dataset contains mobile phone sensor and survey data collected from 46 college students. We used the Pittsburgh Sleep Quality Index (PSQI) (19 self-rated questions including sleep-related behaviors and self-reported sleep quality) administered both at the pre and post study and its scoring rules to categorize each participant as a poor or good sleeper. We use physical activity data collected from participants' phones to compute participants' daily activity levels and patterns. We assess sleep quality detection (good vs poor) using the following inputs: a) participants' textual responses to PSQI questions, b) physical activity-based actograms: visual representations of 24 hour activity levels over days(Fig. 1c), and c) physical activity-based hourly averaged graphs: hourly levels and variations in physical activity (Fig. 1d).

2) Models: We compare various LLMs and traditional machine learning models. LLMs: 1) Zero-shot learning: we feed data (EEG waveform images, spectrograms, or features) into LLMs. No specific training is conducted and the LLMs leverage their pre-existing knowledge. We use two LLM

variants: GPT 4 vision (2024-02-15-preview) for image input and GPT 4 (2023-05-15) for textual input, 2) In-context learning LLM: we include input data and label examples in prompts so that LLMs (GPT 4) learn from context and adapt their response accordingly. 3) Fine-tuned LLM: We finetune LLMs (GPT 3.5 turbo 2024-02-15-preview) using training and validating datasets. A traditional machine learning model, XGBoost uses a technique called gradient boosting that combines simple decision trees for accurate predictions. We also analyze feature importance by looking at the number of times each feature is used for trees. 3) Baseline (majority vote): simply predicts the majority class for all test samples. It serves as a basic reference point to evaluate the performance of other models. For sleep quality detection, we also use the ground truth scoring method based on PSQI. We evaluate model performance using accuracy and weighted F1 score. Please see examples of LLM prompts in the Appendix.

B. Experiment 2: Personalized and adaptive sleep improvement feedback

We explore whether LLMs can generate personalized content for sleep improvement and focus on generating 1) sleep improvement suggestions and 2) guided imagery scripts. To generate the sleep suggestions, we feed LLMs various user context or profile information including a) EEG features from Sleep EDF dataset, b) PSQI answers in Student Life dataset, c) physical activity-based actograms, d) gender, e) age group, f) ethnicity, g) health issues such as "anxiety", "PTSD", "insomnia", "pain", "awakenings during nights", "shift worker", h) user preferences such as favorite environments: beach, forest, favorite animals: dogs, cats; hobbies: traveling, baseball, exercise. To generate scripts to help a person sleep, we prompt the LLM to leverage a Guided Imagery technique [14]. This technique is also known as Guided Visualization, a mindbody technique that involves visualizing positive images or scenarios using all senses to help promote relaxation, manage anxiety, and stress, and enhance well-being. A typical session might include relaxation exercises, quiet sitting or lying down, and focusing on a specific goal. See prompt examples in the Appendix.

III. RESULTS

A. User state detection

1) Attention detection: Table I summarizes attention detection performance. Traditional machine learning models outperformed LLM-based models for attention detection. Among the LLM models, fine-tuned GPT-3.5 models demonstrated the best performance. However, the GPT-4 vision model faced limitations. It failed to infer user states in approximately 25-30% of cases, often returning a generic response such as "As a text-based AI, I do not have the capability to process images and I cannot assist with this request". In addition, when we feed high dimensional EEG features, the GPT model indicated that it requires machine learning models and did not infer user states,

TABLE I: Attention Detection

Models	acc	F1	note
Finetuned GPT3.5 (features)	53.7	0.51	
In-context GPT4v (spectrogram)	55.7	0.56	25% "cannot assist"
In-context GPT4 (features)	50.0	0.57	97% "cannot assist"
Zero-shot GPT4v (spectrogram)	66.2	0.55	30% "cannot assist"
Zero-shot GPT4 (features)	-	-	99% "cannot assist"
XGBoost (features)	91.3	0.93	
Baseline (majority vote)	66.6	0.53	

The fine-tuned GPT3.5 model typically shows high confidence levels of 100%. The model shows information about the power spectrum and ratios (e.g.,delta, theta, alpha, beta, alpha/delta) as the explanations for inference. For example, when correct inference is made with 100% confidence, the GPT 3.5 model explains "The participant is unfocused because the alpha/delta ratio is high and the beta power is low, which are indicative of a relaxed and unfocused state."

Incorrect inferences lack clear explanations and appear based on simple heuristic rules. For example, when ground truth is focused but unfocused is inferred, the model said "The participant's state is unfocused because the alpha/delta ratio for channel AF3 is 0.166027, which is below the threshold for focused state." When ground truth is unfocused but focused is inferred, the model said "The participant is focused because the alpha/delta ratio is high and the beta power is low, which are characteristic of a focused state."

We also analyze feature importance from the XGBoost model and learn that the model uses more variety of features for classifying focus vs unfocus including channel O2 kurtosis, AF4 beta, F3 percent 90, F7 beta, and T8 standard deviation.

2) Sleep stage detection: Table II summarizes sleep stage detection performance. LLM-based sleep detection shows lower performance than ML-based models. GPT 4 vision models (both in-context learning and zero-shot learning) often return a message that they cannot assist with the task. Incontext learning with EEG waveforms performs worse than zero-shot learning with EEG waveforms. In-context learning with EEG features seems more effective than the zero-shot LLM model with EEG features. GPT fine-tuned models show higher misclassification rates compared to XGBoost. For example, they misclassify wake as REM, stage 1 as stage 2, and REM as stage 2. However, stage 2 and stage 3 & 4 are similar (Fig.2).

The fine-tuned GPT 3.5 model shows inference confidence from 20 to 100 % (mean: 79.7 %, median 80%, stdev: 9.7%). The model outputs the explanation that it uses power spectrum and ratio for classifying sleep stages. For example, when the model infers correct stage 3&4 sleep, it outputs "The dominant frequency bands in the EEG signal are delta and theta, with high power in both bands. The alpha and beta power are relatively low. The alpha delta ratio is low, indicating a higher proportion of slow wave activity. The theta alpha ratio is high, suggesting a predominance of theta activity. The delta theta ratio is also high, indicating a higher proportion of slow wave activity compared to theta activity. These features are

TABLE II: Sleep Stage Detection

Models	acc	F1	note
Finetuned GPT3.5 (features)	50.6	0.46	
In-context GPT4v (EEG signals)	25.4	0.21	51% "cannot assist"
In-context GPT4 (features)	44.7	0.40	8% "cannot assist"
Zero-shot GPT4v (EEG signals)	19.2	0.19	13% "cannot assist"
Zero-shot GPT4 (features)	29.0	0.25	0.2% "cannot assist"
XGBoost (features)	75.6	0.74	
Baseline (majority vote)	37.2	0.20	

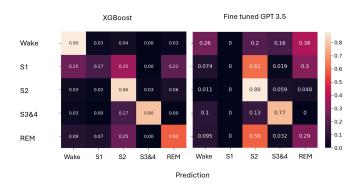


Fig. 2: Sleep stage detection models: confusion matrix

indicative of stage 3 or 4 sleep, also known as slow wave sleep."

The important features extracted from the XGBoost model show kurtosis, mean, standard deviation, and 90th percentile amplitude in addition to power spectrum and ratio features.

3) Sleep quality detection: We compare sleep quality detection (good vs poor sleep; confidence levels) using two approaches: (1) scored by PSQI standard scoring procedure vs. 2) GPT4 (Table III). Overall accuracy of the GPT4 model is 85.7%. There are 11 error cases out of 77. GPT-4 demonstrates relatively good sleep quality detection performance based on textual answers to PSQI; however, GPT-4 struggles to recognize sleep quality accurately when participants show poor sleep behavior (e.g., short sleep, difficulty falling asleep, or disrupted sleep) but good self-reported sleep quality (inference confidence is also low (60-65 %). GPT seems to emphasize subjective sleep quality over answers to other PSQI questions. Confidence levels of the GPT fine-tuned model are 60-100 % (mean: 80% and std: 7.9 %). The confidence level is high when self-reported sleep quality is consistent with sleep behaviors (e.g. very bad self-reported sleep quality and poor sleep related behaviors such as long sleep latency, awakenings during the night, bad dreams, pain, feeling too cold, worry, and difficulty maintaining enthusiasm for daily activities).

LLMs detect sleep and active periods and regular sleep patterns from the physical activity actograms and averaged graphs provided; however, the image data fed into LLMs are recognized as poor sleep. LLMs easily pick up some physical activities during the night time that occurred only a few nights out of 60 days of data and recognize them as a sign of poor sleep. For instance, when the actograms show increased activity after 5 am for a few days out of 60 days of data, suggesting potential wakefulness, LLMs misinterpret

TABLE III: Sleep Quality Detection

PSQI scoring	GPT4 response	# of participants
good	good	39
poor	poor	27
good	poor	0
poor	good	11

this as poor sleep quality. This implies GPT-4's limitations about the challenge of understanding a full range of human sleep behavior and variabilities. Sleep quality is multifaceted and LLMs might not fully grasp the nuances.

B. Sleep Improvement Feedback Generation

LLMs modify suggestions and guided imagery scripts based on user input and profiles (e.g., symptoms, user preferences). Tables V and IV show examples of sleep improvement suggestions and guided imagery scripts based on user profiles.

LLMs generate sleep improvement suggestions that align with cognitive behavioral therapy for insomnia (CBT-i) [15]: (1) consistent sleep schedule, (2) avoid late night activities, (3) avoid fluids close to bedtime, (4) try relaxation techniques to help fall asleep and improve sleep quality, (5) restful room environment (light, temperature), (6) reduce caffeine intake, large meals, alcohol before bed, and (7) regular exercise. LLMs also weave user profiles (e.g. what they like, and issues they have) into generated guided imagery scripts and change scenes and phrases.

When we feed EEG features for generating guided imagery scripts, if we just simply ask LLM to generate a script based on EEG features, LLM incorporates numerical information into guided imagery scripts such as "As you sink deeper into this state of relaxation, there is a harmonious balance between theta and alpha waves with a ratio of 2.3. "For users, hearing specific numerical information about EEG features might not be useful because they might not know how those numbers are associated with their states, therefore, we adjust prompts not to include numerical information in the generated guided imagery script (Table V, Appendix for a prompt example). Further tuning of prompt design and evaluation are required to generate effective adaptive feedback. Sleep improvement suggestions do not change based on EEG features because suggestions are not based on momentary EEG features but habitual sleep related behaviors.

IV. DISCUSSION

This work explores the usage of LLMs and physiological and behavioral sensor data for attention and sleep detection and sleep improvement. Our experiments highlight both LLMs' strengths and limitations.

LLM-based attention and sleep detection exhibit lower performance compared to traditional ML models. Fine-tuned LLMs improve models' ability to handle diverse contexts. However, we also found limitations. The fine-tuned GPT3.5 model uses limited features (e.g. power spectrum density and ratio) for classification even after fine-tuning and GPT-4 vision models fail to handle visual input. Also, feeding

high dimensional numerical features such as EEG features to LLMs does not reliably estimate user states. To improve human state detection, LLM's knowledge needs to be extended beyond simple one-on-one relationships such as increased alpha band activity during unfocused state and LLMs require further refinement to handle diverse human physiological and behavioral data, variabilities, and patterns effectively. This might be possible using fine-tuning with larger datasets and retrieving external sources of knowledge. In addition, textual knowledge might not fully capture complex physiological and behavioral patterns; therefore, integrating textual information with numerical and visual data is essential in order to understand variability within and across individuals; however, the capacity of current LLM vision models and fine-tuning is still limited and LLMs requires much diverse data to enhance the knowledge.

LLM-based sleep improvement suggestions and guided imagery scripts are personalized and adaptive to user profiles. Automatically generated suggestions and scripts have a potential for AI-based conversational systems or intervention systems after effectiveness and safety are carefully tested.

There are several limitations in this study. First, this study is an early exploration with limited datasets and limited LLMs. Refining prompts and using large and diverse datasets might help enhance task performance. We intentionally use interpretable features rather than low dimensional embeddings to test the extent to which LLM internal knowledge contributes to altered state detection and improvement. Our study only relies on public datasets and offline experiments; therefore, user studies with end users and clinicians are necessary to evaluate generative responses in terms of accuracy, effectiveness, and safety. Lastly, beyond LLMs, there are other advanced approaches such as transformer models and multimodal learning for detecting user states.

We also discuss the ethical considerations of using LLMs to detect and improve human-altered states. First, feeding personal physiological and behavioral data to LLMs could raise privacy concerns. Users might worry about the security and confidentiality of their sensitive information. Transparent consent processes and reliable data anonymization are important. Second, LLMs are trained on massive data that might contain biases. Bias detection and mitigation strategies are necessary to ensure fair outcomes. LLMs might have the capability to generate unethical, harmful, or inaccurate content or manipulate individuals. Implementing guidelines for responsible use and monitoring LLM-generated content are required.

REFERENCES

- [1] D. J. Buysse, "Sleep health: can we define it? does it matter?" *Sleep*, vol. 37, no. 1, pp. 9–17, 2014.
- [2] J. A. Horne and L. A. Reyner, "Sleep related vehicle accidents," *Bmj*, vol. 310, no. 6979, pp. 565–567, 1995.
- [3] M. R. Rosekind, K. B. Gregory, M. M. Mallis, S. L. Brandt, B. Seal, and D. Lerner, "The cost of poor sleep: workplace productivity loss and associated costs," *Journal of Occupational and Environmental Medicine*, vol. 52, no. 1, pp. 91–98, 2010.

TABLE IV: GPT4-generated sleep improvement suggestions

Profiles	LLM-generated Suggetsions
Headaches disturb sleep	Check with a medical professional about the headaches to see if they can be treated
Trying to solve coding problems in bed	Avoid activities such as coding which could generate stress and disrupt sleep
Bed feels uncomfortable	Maybe consider investing in a new mattress or bedding if your current one feels uncomfortable
Stress	Engagement in stress-relieving activities such as yoga, mindfulness,
	and deep-breathing can help in reducing stress levels which can improve sleep quality
OCD	Consultation with a Sleep Specialist or mental health professional may also be beneficial,
	especially since OCD was mentioned as a reason for troubled sleep

TABLE V: GPT4-generated guided imagery scripts

Profiles	LLM-generated Guided Imagery Scripts
Like Beach	Close your eyes and imagine yourself on a peaceful beach; Begin with lying down in a comfortable position. Close your eyes and take a couple of deep breaths, inhaling and exhaling gradually. Visualize the calming view of a beach, the sand beneath your feet, the tranquil waves that are rhythmically kissing the shore. Feel the warmth of the sun on your skin, the softness of the sand as it molds perfectly to your feet. Hear the distant sound of seagulls, the gentle lull of the waves. Breathe in the refreshing, salty sea air. With every breath you take, your body feels lighter and sleepier. Let this calming beach imagery help to lower your heart rate and help you drift off to sleep.
Like Family	Close your eyes and imagine you're sitting in a cozy, comfortable family room. The room is warm, inviting, and filled with soft, dimmed light that creates a soothing atmosphere; This scene prompts feelings of relaxation, comfort, and safety, associated with being surrounded by loved ones. You see all your loved ones gathered, chatting, and enjoying each other's company. There's a gentle hum of relaxed conversation and soft laughter, the sounds of your family's voices proving to be the most calming sounds you've ever heard; Hearing familiar voices has been shown to reduce stress and anxiety, allowing your mind to unwind and merge into a relaxation state suitable for sleep. You feel an overwhelming sense of love, joy, and peace as you sit there surrounded by the people who matter the most. Outside the room, you see through the window that it's nighttime with a sky full of stars and the moon shining brightly, creating a perfect scenery indicating it's time for you to sleep
PTSD	Imagine you're in a beautiful, peaceful forest; Begin by closing your eyes and taking several deep breaths, in through the nose and out through the mouth. As you continue these slow, deep breaths, begin to visualize yourself standing at the edge of a beautiful, calm forestThis forest is your safe space, a haven untouched by past trauma. You can stay here as long as you need, resting in the peaceful ambiance. No harm can find you here. Continue to cultivate this sense of peace and safety with each deep, calming breath
Insomnia	Imagine yourself in a serene, beautiful forest; As insomnia has been bothering you, positive visualization can aid in releasing negative energy and reduce stress
Shift workers	Relaxing Beach Journey; Begin by making yourself comfortable. Slowly take a deep breath in and as you exhale, close your eyesFor a shift worker, building a regular sleep schedule can be tough. Guided imagery can aid in achieving a relaxed state quicker once in bed, making the most of the sleep time available
EEG features	You are now entering the first stage of sleep, a stage of light sleep. This slow transition into sleep is marked by the gentle wave-like rhythm of your alpha and theta powers. Your consciousness begins to dissolve into a calm and cloud-like tranquility

- [4] R. Richer, N. Zhao, J. Amores, B. M. Eskofier, and J. A. Paradiso, "Real-time mental state recognition using a wearable eeg," in 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE, 2018, pp. 5495–5498.
- [5] T. Baltrušaitis, D. McDuff, N. Banda, M. Mahmoud, R. El Kaliouby, P. Robinson, and R. Picard, "Real-time inference of mental states from facial expressions and upper body gestures," in 2011 IEEE international conference on automatic face & gesture recognition (FG). IEEE, 2011, pp. 909–914.
- [6] M. Vidal, J. Turner, A. Bulling, and H. Gellersen, "Wearable eye tracking for mental health monitoring," *Computer Communications*, vol. 35, no. 11, pp. 1306–1311, 2012.
- [7] S. A. Imtiaz, "A systematic review of sensing technologies for wearable sleep staging," *Sensors*, vol. 21, no. 5, p. 1562, 2021.
- [8] J. C. Shin, J. Kim, and D. Grigsby-Toussaint, "Mobile Phone Interventions for Sleep Disorders and Sleep Quality: Systematic Review," JMIR mHealth and uHealth, vol. 5, no. 9, p. e7244, Sep. 2017, company: JMIR mHealth and uHealth Distributor: JMIR mHealth and uHealth Institution: JMIR mHealth and uHealth Label: JMIR mHealth and uHealth Publisher: JMIR Publications Inc., Toronto, Canada. [Online]. Available: https://mhealth.jmir.org/2017/9/e131
- [9] J. W. Kim, A. Alaa, and D. Bernardo, "Eeg-gpt: Exploring capabilities of large language models for eeg classification and interpretation," arXiv preprint arXiv:2401.18006, 2024.
- [10] Y. Kim, X. Xu, D. McDuff, C. Breazeal, and H. W. Park, "Health-Ilm: Large language models for health prediction via wearable sensor data," arXiv preprint arXiv:2401.06866, 2024.
- [11] Ç. İ. Acı, M. Kaya, and Y. Mishchenko, "Distinguishing mental attention states of humans via an eeg-based passive bci using machine learning

- methods," Expert Systems with Applications, vol. 134, pp. 153-166, 2019
- [12] B. Kemp, A. Zwinderman, B. Tuk, H. Kamphuisen, and J. Oberye, "Analysis of a sleep-dependent neuronal feedback loop: the slow-wave microcontinuity of the eeg," *IEEE Transactions on Biomedical Engineering*, vol. 47, no. 9, pp. 1185–1194, 2000.
- [13] R. Wang, F. Chen, Z. Chen, T. Li, G. Harari, S. Tignor, X. Zhou, D. Ben-Zeev, and A. T. Campbell, "Studentlife: assessing mental health, academic performance and behavioral trends of college students using smartphones," in *Proceedings of the 2014 ACM international joint conference on pervasive and ubiquitous computing*, 2014, pp. 3–14.
- [14] J. Utay and M. Miller, "Guided imagery as an effective therapeutic technique: A brief review of its history and efficacy research." *Journal* of *Instructional Psychology*, vol. 33, no. 1, 2006.
- [15] S. G. Hofmann, A. Asnaani, I. J. Vonk, A. T. Sawyer, and A. Fang, "The efficacy of cognitive behavioral therapy: A review of meta-analyses," *Cognitive therapy and research*, vol. 36, pp. 427–440, 2012.

APPENDIX

Prompt and LLM response examples

Zero-shot learning:

"You are a data analyst who reviews EEG data and helps interpret participant's conditions. Please review the power spectrum data of EEG data. The data has an x-axis of time and a y-axis of frequency (0-40 Hz). The data is collected from healthy

participants who went through cognitive tasks. We would like to classify the user state into 2 categories: focused or unfocused, confidence level (0-100%), and explanations. Please return your response in JSON format."

In-context learning:

Please review the following 6 EEG data. The data has an x axis of time and a y axis of amplitude. The data is collected from healthy participants who went through sleep. The first 5 images were collected during wake state (W), stage 1, stage 2, stage 3&4, and REM sleep. Please provide 1. a description of each image 2. estimate the sleep stage of the 6th (last) image and return a number from 0 to 5 (0:wake, 1: stage 1, 2: stage 2, 3: stage 3 or 4, 4: REM, 5: unknown or movement) 3. confidence level (0-100%) 4. explanations in JSON format.

Sleep quality detection:

"You are a data analyst helping a neurologist understand human sleep data. Task: This is the data collected from users who fill out the Pittsburgh Sleep Quality Index questionnaire. Based on this data, please give me the following information. (1) if this person has good sleep quality or poor quality (2) confident level (0-100%) (3) explanations for the decision. (4) suggestions to improve sleep quality."

Sleep quality detection:

"Please review the following graph made from smartphone activity sensor data. The data has an x-axis of time (midnight to midnight) and a y-axis of date. For each hour, we computed the mean of activities where 0: Stationary, 1: Walking, 2:Running, 3:Unknown. Please describe (1) estimated sleep quality (good or poor) (2) confidence (0-100(3) explanations (4) suggestions to improve sleep quality in JSON format."

Suggestion to improve sleep/Guided Imagery:

"You are a sleep therapist. The participant is [participant conditions/profiles]. Reflecting on the participant's profile, please generate suggestions (a guided imagery script) to help the participant sleep better."

Sleep Guided Imagery using EEG features:

"You are a sleep therapist. Please generate a guided imagery script based on the following 30-s epoch EEG features, alpha, beta, delta, theta, gamma power, alpha delta ratio, theta alpha ratio, delta theta ratio, mean, standard deviation, kurtosis, 90th percentile of amplitude. Do not include actual numerical EEG features, brain waves, power spectrum, or different frequencies of waves in the script but include the state estimated from the features."