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Neural Complexity and Prognosis: Predicting Recovery in Pediatric Epilepsy Using EEG Markers

Abstract

Predicting patient functional outcomes is an indispensable part of clinical care in the Pediatric Intensive Care Unit (PICU), especially for children with epilepsy, a prominent neurological emergency. Electroencephalography (EEG) is a dynamic tool for assessing brain activity, with brain complexity and spectral power features emerging as predictors of consciousness recovery. We investigated whether patients' EEG activity under anesthesia could predict their recovery, using data from 12 pediatric epilepsy patients (mean age: 11.0±2.2 years). Neural complexity, the intricacy of connectivity between brain regions, is heavily implicated in a patient's capacity for consciousness. We hypothesize that neural complexity will be a stronger predictor of patient outcomes than spectral power and that higher complexity will be associated with better outcomes. EEG features were analyzed during sedated, baseline (non-sedated), and difference states. Recovery was assessed three months post-injury using the Glasgow Outcome Scale-Extended (GOS-E). The predictive performance of significant EEG markers was evaluated using logistic regression with leave-one-out cross-validation and permutation testing. Baseline EEG features showed minimal prognostic power, whereas sedation and difference states yielded high prognostic accuracy. In the sedated state, the complexity features rate entropy and Lopez-Ruiz-Mancini-Calbet Complexity (HC-LMC) predicted recovery, separating good and poor outcomes with 100% accuracy. These findings demonstrate that EEG markers of complexity can predict the recovery of consciousness in pediatric epilepsy patients under anesthesia. Therefore, EEG analysis could be an accessible, accurate, and powerful prognostic tool in clinical settings. Future research should explore these results in larger samples to validate the findings that rate entropy and HC-LMC are predictive of recovery. Further, these features should be studied in patients of different etiologies to analyze their potential as generalizable markers of consciousness.

Introduction

An unresponsive, brain-injured patient's capacity for consciousness is an integral component of their prognosis. Accurate, efficient prognostication allows clinicians to develop informed care strategies and recovery plans. The need for a powerful tool to assess the recovery of consciousness is particularly evident in the Pediatric Intensive Care Unit (PICU), which provides care to children with critical conditions that often lead to states of unconsciousness. Epilepsy, a common reason for admission to the PICU, is a condition characterized by frequent seizures caused by abnormal electrical activity in the brain. Seizures cause transient or prolonged disruptions in consciousness and are the most prevalent childhood neurological emergency[1,2].

Neural complexity, the complexity of the brain's connectivity, is a key framework for understanding consciousness. Early studies suggest that high complexity necessarily supports awareness[3]. This idea has been corroborated by recent studies showing that brain signal complexity correlates with consciousness levels: in both electroencephalography (EEG) and functional magnetic resonance imaging (fMRI) analysis, complexity decreased with anesthesia-induced unconsciousness[4,5].

Anesthesia is commonly administered to PICU patients for sedation and pain management, and neural changes with anesthesia-induced unconsciousness can be monitored with EEG (a non-invasive measure of the brain's electrical activity)[6,7]. These changes arise from the brain's reconfiguration with anesthesia, adapting to a new physiological environment by shifting connectivity. In the injured adult brain, the extent of this reconfiguration reflects the brain's capacity to recover consciousness[8]. Therefore, assessing the brain's EEG signature under anesthesia is a promising method of predicting a patient's recovery.

EEG is often used to assess the neural status of patients with epilepsy[1,9]. Disruptions of consciousness during epileptic seizures are correlated with a loss of EEG complexity[10]. This finding supports the conclusions from anesthesia research: a loss of consciousness is associated with reduced neural complexity. As shown with anesthesia-induced unconsciousness, a behaviourally unresponsive patient's EEG activity can reveal their underlying capacity for consciousness, highlighting EEG as a powerful prognostic tool[11].

Many EEG features correlate to a patient's capacity for consciousness. In an EEG signal, spectral power measures the strength of brain activity within different characteristic frequency bands: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (>30 Hz). Spectral power, in particular alpha power, has emerged as a prominent feature in discerning a patient's capacity to recover consciousness[12]. Anesthesia induces a state of altered consciousness, causing a shift in power from higher frequency (beta, alpha) to lower frequency (theta, delta) spectral bands in EEG recordings[13]. However, recent research suggests that alpha power may be a marker of consciousness specific to anoxic patients, whose injuries are caused by a lack of oxygen to the brain[14]. Therefore, the need for diverse and comprehensive markers of consciousness is evident.

The Perturbational Complexity Index (PCI), currently a leading method to discern a patient's level of consciousness, measures the complexity of in-

formation in an EEG signal[15]. PCI evaluates the complexity of EEG signals after transcranial magnetic stimulation (TMS), a technique that uses magnetic pulses to stimulate the brain. This method differentiates between levels of consciousness with high accuracy[16]. However, PCI is limited by its high computational complexity and the scarce clinical availability of TMS machines, highlighting the need for accessible measures of consciousness[17,18].

We propose anesthesia as an effective perturbational mechanism to assess EEG signal complexity. This method is clinically accessible, taking advantage of existing conditions in the PICU: continuous EEG monitoring and anesthetic infusion. We aim to use these clinical conditions to explore how a patient's EEG activity changes with anesthesia—can EEG features predict recovery? Our objective is to develop a tool that uses EEG markers to assess the capacity for a return of consciousness in epileptic pediatric patients.

We analyzed various features of EEG complexity and spectral power during baseline (non-sedated) and sedated states, observing if these measures predicted the recovery of consciousness. Baseline states were taken when the patient was not experiencing active seizures, either before or after sedation depending on the availability of recordings. We further considered the prognostic potential of neural reconfiguration under anesthesia, looking at the difference in EEG activity between the baseline and sedated states. Our goal is to extend findings in adults to pediatric patients, exploring whether EEG markers of consciousness can predict functional outcomes. We hypothesize that worse outcomes will be correlated with lower neural complexity, aligning with the findings that high complexity supports consciousness[3–5,10]. We aim to find accessible prognostic markers in epileptic pediatric patients to improve clinical outcomes and advance the understanding of consciousness recovery in the PICU.

Methods

Participant Selection

Participants were selected from an EEG dataset of 41 pediatric patients with a variety of brain injuries, collected in the McMaster Children's Hospital PICU. These patients were given sedatives at different dosages, including midazolam, propofol, and fentanyl. To observe meaningful neural trends, we only used sedation recordings known to alter EEG activity: propofol and midazolam. Propofol and midazolam act through GABA-A receptors, increasing the effects of the inhibitory neurotransmitter GABA to reduce brain activity[19,20]. Fentanyl is used for pain management and does not suppress brain activity to the same extent as propofol and midazolam. Therefore, a recording containing only fentanyl was considered a baseline state.

Patients' three-month outcomes were measured with the Glasgow Outcome Scale-Extended (GOS-E), a scale from 1 (patient death) to 8 (upper good recovery) used to assess functional outcomes[21]. Our inclusion criteria were [1] epilepsy etiology, [2] over five years old, [3] available baseline and sedation recording, [4] available three-month GOS-E measurement, and [5] good quality EEG data. After selection, twelve participants remained.

The demographics of the participants are as follows: six females and six males with a mean age of 11.0±2.2 years (range: 8.0-14.0 years), ten participants with midazolam infusion and two with propofol infusion, seven participants with good recovery (GOS-E $\geq$ 7) and five with poor recovery (GOS-E < 7) recorded three months post-injury. We defined a GOS-E threshold of $\geq$ 7 as the recovered group and < 7 as non-recovered.

Upon admission to the PICU, eight participants presented with status epilepticus, an emergency characterized by long or repeated seizures. Of the remaining four participants, three presented with acute seizures, but it is unclear whether they met the criteria for status epilepticus. The final participant had systemic injuries related to seizure events. Five participants had a previously established diagnosis of epilepsy, whereas seven participants were either new onset or had an uncertain epilepsy history. The majority of patients likely have generalized seizures, affecting large parts of the brain. However, two participants presented with features that may suggest focal epilepsy: one participant with Sturge-Weber syndrome, commonly associated with focal seizures, and another participant with a temporal-parietal abscess who also likely had focal seizures.

Sedation Considerations

Each participant's sedation recording is within 50 hours of their baseline recording. Propofol and midazolam have different effects on EEG, particularly within the beta frequency band that is associated with fast, short wavelength EEG frequencies[22,23]. Midazolam can increase beta spectral power, contrasting with reduced beta spectral power observed with propofol sedation. However, at lower drug doses (sedative doses), propofol and midazolam have similar effects on EEG activity. As mentioned, both drugs act on the same receptor to yield neural inhibition. Therefore, we included participants with either midazolam or propofol sedation to observe if general neuronal inhibition, irrespective of the specific drug mechanism, could predict the recovery of consciousness.

A high sedative dose was preferentially chosen for study inclusion in participants with multiple sedation recordings, as it yields more significant neural change. Infusions were within a typical PICU sedation maintenance range[13]. Midazolam doses ranged from 1-6 µg/kg/min, and propofol doses were between 1-4 mg/kg/hr. Most participants had a dose on the higher end of these ranges, and the doses were similar between the recovered and non-recovered groups. While the participant with the propofol infusion of 4 mg/kg/hr fell slightly outside of the standard sedative range, this variation did not meaningfully impact the results. The specific dose selected for each participant is noted in Supplementary Table 1.

EEG Preprocessing

EEG data was recorded with a 26-channel system, where 26 electrodes were placed around participants' scalps to record whole-brain electrical activity. These electrodes were placed in the standard 10-20 system arrangement that distributes electrodes across the scalp. This data was collected in the McMaster Children's Hospital PICU. Recordings ranged between 7-30 minutes long. Data was preprocessed prior to further analysis, a common EEG technique to remove non-physiological noise. Preprocessing generally contains the same standard steps: filtering out extremely high and low-frequency data (known to be non-physiological), selecting a reference electrode whose activity is used as a baseline for other electrodes, and fragmenting the EEG recording into shorter segments (epochs) for a more fine-tuned analysis. An example of our EEG data segmented into epochs is shown in Figure 1C, where each horizontal line indicates the data from one electrode, and the dotted vertical lines isolate 10-second data stretches (our epoch length).

Our preprocessing pipeline used Python tools (MNE, NumPy, Pandas, SciPy, AutoReject[24]). We performed Independent Component Analysis (ICA), a technique to find and remove EEG components related to eye and heart activity that could introduce electrical noise into the recordings. Examples of components found with ICA are shown in Figure 1A, where red indicates positive activation and blue indicates negative activation. Scalp regions that have more intense colour have higher activity. A component caused by an eye blink will have high activity in the frontal electrodes (near the "nose" in the scalp schematic in Figure 1A). Components originating from non-brain sources, such as eye blinks, were identified and removed

before reconstructing the EEG signal. We then used the EEG-specialized machine learning tool AutoReject to automatically detect, interpolate, and remove particularly noisy epochs.

We filtered out low and high frequencies to yield recordings with activity between 0.5-45 Hz. We further applied a notch filter, a filter used to drastically decrease the strength of a signal at a target frequency, at 60 Hz. 60 Hz corresponds to the AC electrical power of North America, appearing as significant electrical noise in the EEG signal. The Mastoid electrodes are located near the ear and do not generally record high levels of brain activity. Therefore, we set the Mastoid electrodes as references, with their activity serving as a baseline from which to analyze other electrodes.

We inspected each recording's Power Spectral Density (PSD) plot, which shows how power (y-axis) is scattered across frequencies (x-axis). Example PSD plots are shown in Figure 1C and Figure 1D. A high-power value at a given frequency indicates that frequency is prominent in the EEG signal. Through visual analysis of these plots, we identified many high-power peaks around 28 and 44 Hz. These peaks were likely induced by medical equipment in the PICU. The peak parameters (power, width, and frequency) were identified with the power spectrum modelling software Fitting Oscillations and One Over F (FOOOF), a Python package used to find key power and frequency characteristics of EEG signals[25]. We used a notch filter to remove the peaks at 28 and 44 Hz, adjusting the power of the filter to the size of the peak. Electrodes that contained excessive noise not removed during prior preprocessing were identified, and up to 25% of electrodes were removed per recording to improve data quality.

Results show successful noise reduction and improved signal quality post-preprocessing. The dataset contains 145 recordings from 12 participants. Four recordings failed the preprocessing pipeline due to excess noisy epochs. Within the remaining data, 4.69% of all EEG electrodes were removed.

EEG Analysis

We calculated 12 spectral power and 27 complexity features for each epoch and electrode in the EEG recordings. We then calculated the median value for each feature across all epochs and electrodes, ensuring we had only one value per feature for each participant for simplicity of analysis. Further analysis was performed with these median values to compare time-averaged EEG feature values with patient recovery. The 12 power features included the relative and absolute spectral power values for the previously mentioned characteristic frequency bands (delta, theta, alpha, beta, and gamma). Additional power features were the slope and slope offset of the PSD plots, measures of how spectral power decays with increasing frequency (see examples of this frequency-dependent decay in Figures 1C and 1D). Complexity features were a range of neural complexity and entropy features implicated in signal processing and consciousness science. Some examples are Lempel-Ziv complexity (LZC), Permutation entropy, and Shannon Entropy.

We plotted each feature's value against GOS-E with a linear regression line and calculated the Pearson correlation coefficient (r) to assess the strength of a linear relationship between two variables. We further calculated the R^2 and p-value of the Pearson correlation, which indicate whether the linear model is a good fit to the data and the significance of the observed relationship, respectively. R^2 is a value between 0 and 1, with values closer to 1 indicating a stronger fit of the model to the data. The p-value is a measure of statistical significance, where smaller p-values indicate greater significance (with $p < 0.05$ often used as a cutoff).

The R^2 value was validated using leave-one-out cross-validation. This technique evaluates the linear model's fit by sequentially removing individual data points and assessing the model's performance on the omitted data. Cross-validation allows for a more thorough analysis of the relationship between GOS-E and EEG features; a correlation with a high R^2 but low validated R^2 indicates that the correlation is well fitted to the present data but may not generalize well to new data (overfitting). We performed this linear analysis three times, looking at trends in the baseline state, sedated state, and the absolute difference between the baseline and sedated states (difference state).

Subsequently, we divided participants into recovered and non-recovered groups. Differences between recovery groups for each EEG feature were assessed with a Mann-Whitney U test, which uses the test statistic U to evaluate whether the distributions of two groups differ significantly. The Mann-Whitney U test was performed on the baseline, sedated, and difference states. A p-value of < 0.05 was used to evaluate whether the differences observed in the Mann-Whitney U test were statistically significant. Features that yielded significant U values had better separability between groups and were selected for further analysis.

These significant features were used in logistic regression, a machine-learning technique that calculates the probability of an instance belonging to one of two classification categories. We trained a logistic regression to determine whether a patient was recovered (high GOS-E) or non-recovered (low GOS-E) from EEG features. We tested different combinations of features to find those that yielded the highest predictive accuracy. After finding this combination, we modified the logistic regression to enhance performance by normalizing EEG features to the same scale and adjusting the model's hyperparameters (adjustable settings which control the model's behaviour and complexity). We found that the ideal hyperparameters were those that reduced the model's complexity, ensuring it generalizes well to new data, and used a regression algorithm well suited for small datasets. The model was validated with leave-one-out cross-validation.

The 95% confidence intervals for accuracy and the area under the Receiver Operating Characteristic (ROC) curve (AUC-ROC) were calculated to evaluate the model's performance. AUC-ROC quantifies how well a model distinguishes between two groups, with higher values indicating better discrimination. Confidence intervals provide a range of values for these metrics, indicating the model's reliability and generalizability. To estimate these intervals, we used bootstrapping—a resampling technique that repeatedly tests random subsets of the data to assess the model's reliability. We used bootstrapping with 1000 iterations to obtain a stable measure of the confidence intervals without using excessive computational resources. The significance of the accuracy and AUC-ROC was assessed with a permutation test, which evaluates whether the results are statistically meaningful by randomly shuffling data and recalculating outcomes over 1000 iterations.

Many participants have several EEG recordings with different sedative doses. As previously discussed, we selected the highest available sedative dose within the typical PICU sedation range for study inclusion. To validate our dosage selection method and the logistic regression's performance, we ran a series of logistic regressions with randomized sedative EEG recordings selected from a participant's available recordings. This analysis helps reveal whether higher sedative doses are optimal for EEG investigation. For each participant, a random recording within the typical PICU sedative range was selected. The range of available sedation doses for each participant is noted in Supplementary Table 1. These recordings were then subject to logistic regression with the same parameters as previously outlined, and the accuracy and AUC-ROC were assessed. We repeated this randomization 1000 times and calculated the average accuracy and AUC-ROC across all trials. This additional analysis helps to better understand the prognostic capabilities of anesthetic infusion, regardless of the selected dosage.

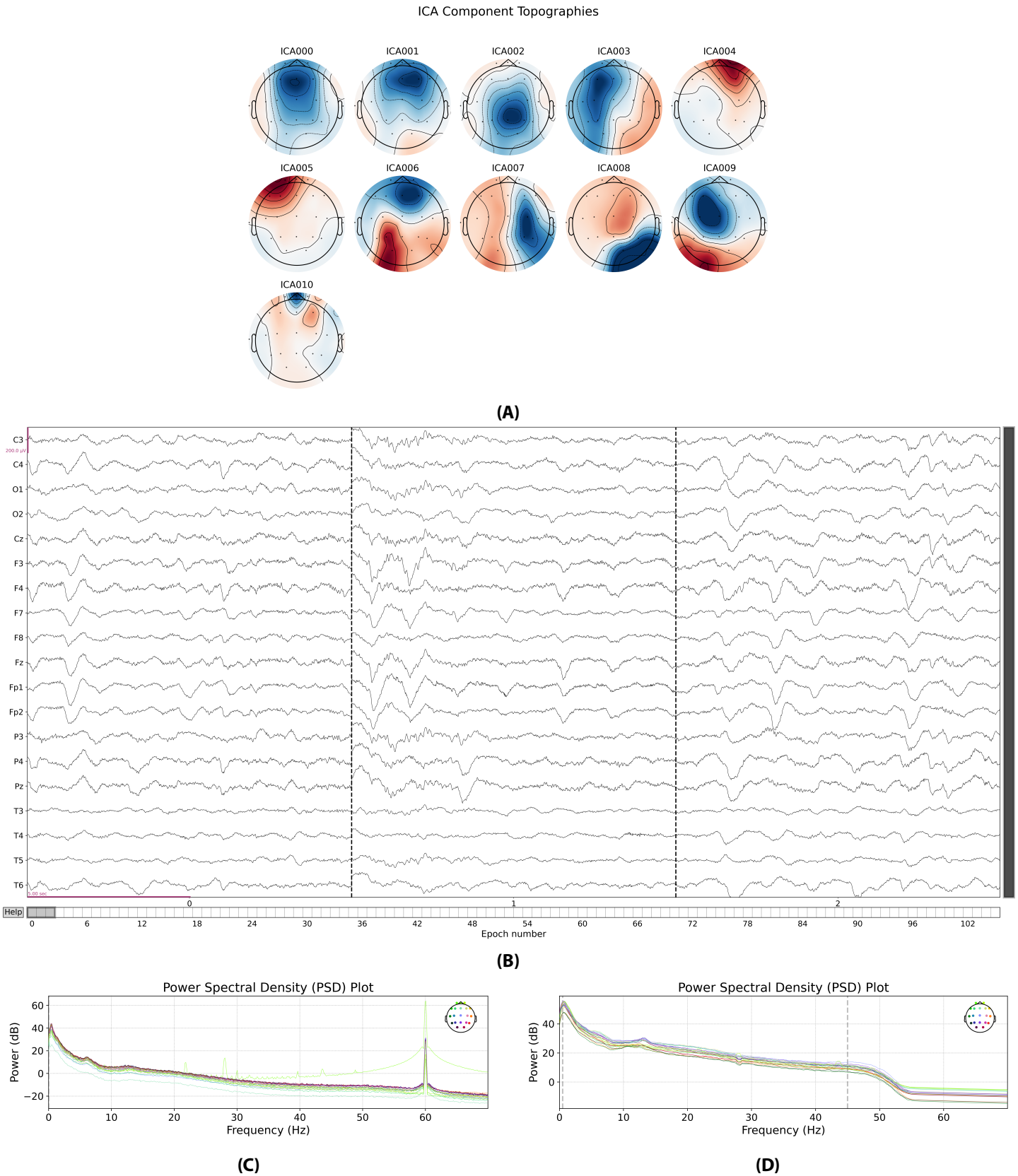

Figure 1. Visualization of the preprocessing pipeline for an example EEG recording. (**A**) Independent Component Analysis (ICA) to identify different components of activity across the scalp. Red regions represent positive activation, and blue regions represent negative activation. Higher opacity indicates greater activity in that area. (**B**) Time series of EEG activity segmented into epochs, showing multi-channel brain activity. The horizontal axis represents different 10-second epochs, while the vertical axis shows different EEG electrodes. Each line shows how voltage in a given electrode varies over time. (**C**, **D**) Power Spectral Density (PSD) plots of the example EEG recording before (left) and after (right) preprocessing. The x-axis represents frequency (Hz), and the y-axis shows spectral power (dB). Notably, preprocessing reduced the large peak of noise at 60 Hz.

Results

Baseline Analysis

None of the power or complexity features calculated from the baseline (non-sedated) recordings were significant linear predictors of participants' GOS-E scores. One complexity feature, Permutation LZC, yielded significant differences between low and high GOS-E groups (U=30.0, p=0.048). Permutation LZC is a complexity feature that looks at nonlinear signal variability in an EEG signal[26]. We did not find any other results of interest in the baseline state, so we did not pursue further analysis of these recordings.

Difference Analysis

The perturbation of the brain under anesthesia (absolute difference between the baseline and sedated state) yielded several significant linear trends. Although none of the power features were significant linear predictors of participants' GOS-E scores, we found seven complexity features that were significantly correlated with GOS-E, including Approximate entropy (a measure of pattern predictability designed for physiological data) and Shannon entropy (a foundational entropy metric that assesses the amount of information in a signal)[27]. All linear trends had a negative coefficient, indicating that smaller changes in complexity between baseline and sedation states are predictive of higher GOS-E. While many of these features yielded strong linear trends, their cross-validated R^2 values were poor, indicating that the observed trends do not generalize well to new data.

There were significant differences between low and high GOS-E participants' alpha power using a Mann-Whitney U test (U=30.0, p=0.048). We found two complexity features that yielded significant GOS-E group differences. These results demonstrate that the perturbation of the brain under anesthesia may predict patient recovery. While the complexity features had a negative relationship with GOS-E (i.e., a smaller change in complexity correlated with a higher GOS-E), alpha power had a positive trend; greater differences in alpha power between baseline and sedation were associated with greater recovery.

Sedation Analysis

The most significant results, both linearly and with group differences, are in the sedated state. Twelve complexity features had significant Pearson correlations with participants' GOS-E scores. Most of these trends persisted after cross-validation, indicating good generalizability. Twelve complexity features and three power features yielded significant differences between low and high GOS-E groups. These included relative and absolute beta power, relative delta power, Permutation entropy, and LZC among others (see Supplementary Tables 2 and 3 for more examples).

Specifically, complexity features rate entropy and Lopez-Ruiz-Mancini-Calbet Complexity (HC-LMC) separated all participants on a single-subject level between recovered and non-recovered groups. Rate entropy and HC-LMC had strong linear trends and high cross-validated R^2 values of 0.503 and 0.566, respectively, indicating they are highly predictive of patient recovery. Rate entropy positively correlated with good recovery, whereas HC-LMC negatively correlated with recovery. These two relationships are shown in Figure 2, and violin plots of the features separated into GOS-E groups are shown in Figure 3. Violin plots provide a visual representation of the distribution and variability of rate entropy and HC-LMC across GOS-E groups, highlighting differences between recovered and non-recovered patients. For example, in Figure 3, we see differences in rate entropy and HC-LMC for low and high GOS-E groups, which express an inverse relationship between these features.

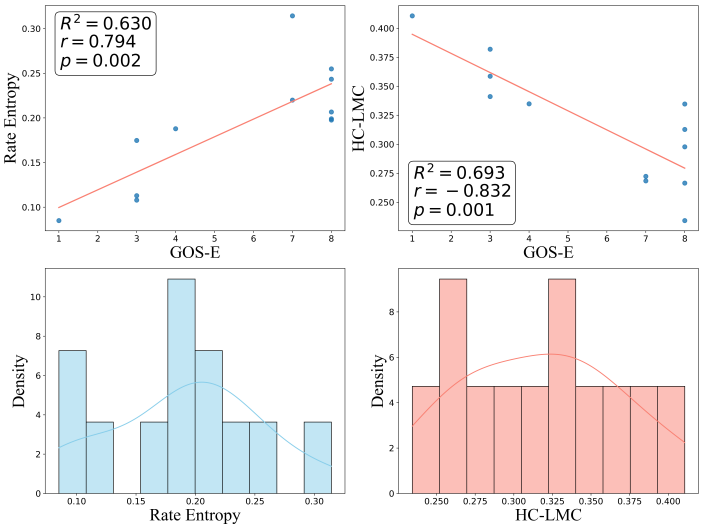

Figure 2. Relationships between EEG complexity features and patient recovery under sedation. (Top Left) Rate entropy vs. GOS-E. A strong positive correlation indicates that higher entropy rates are associated with better recovery. (Top Right) Lopez-Ruiz-Mancini-Calbet Complexity (HC-LMC) vs. GOS-E. A strong negative correlation suggests that lower HC-LMC values are predictive of better recovery. Pearson's correlation coefficient, line goodness-of-fit, and the linear relationship's significance are shown for each scatter plot. Histograms showing the distribution of each metric across patients are shown under the scatter plots.

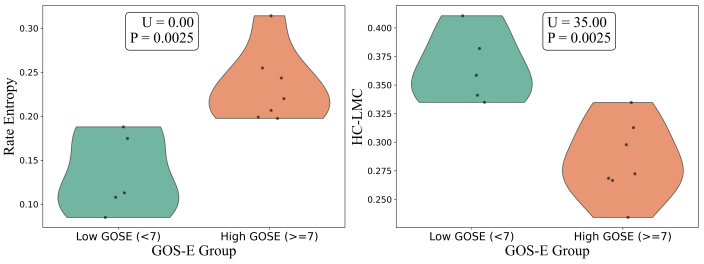

Figure 3. Comparison of EEG complexity features between patients with poor (GOS-E < 7) and good (GOS-E ≥ 7) recovery outcomes. (Left) Violin plot of rate entropy in the two recovery groups. Patients with better outcomes exhibit significantly higher Rate Entropy values (Mann-Whitney U=0.00, p=0.0025). (Right) Violin plot of HC-LMC across recovery groups. Patients with better outcomes show lower HC-LMC values (Mann-Whitney U=35.00, p=0.0025).

Logistic Regression

We found that the combination of HC-LMC and rate entropy, recorded with sedation, gave the highest accuracy in logistic regression. The model correctly classified 100% of cases, with an AUC-ROC of 1.00 (95% CI: 1.00-1.00). The model performed worse with additional EEG features, indicating that the model favours simplicity over complexity. The permutation test p-value was 0.0010 for AUC-ROC and 0.0020 for accuracy, both highly significant results. These results suggest that the observed separability of low and high GOS-E with HC-LMC and rate entropy is unlikely to be due to chance.

Using the same logistic regression hyperparameters with HC-LMC and rate entropy as features, we randomized the sedation dose for each participant. After repeating the logistic regression 1000 times with random sedative doses, the model correctly classified an average of 80.33% of cases (95% CI: 70.72%-80.95%), with an AUC-ROC of 0.777 (95% CI: 0.769-0.785).

Discussion

We explored the prognostic potential of various EEG features of spectral power and complexity for both baseline (non-sedated) and sedated states, considering whether baseline, sedation, or the difference between the two states' features (due to neural reconfiguration) was most predictive of recovery. We found that the baseline state has little prognostic power, and the difference state had some predictive capability. However, the linear trends seen in the difference state did not persist after validation, indicating they may result from overfitting. We found some ability to discriminate between low and high GOS-E in the difference state, suggesting that changes in the brain with anesthesia may predict the recovery of consciousness. However, more work is needed to validate these trends in larger sample sizes.

Overwhelmingly, we found the most substantial prognostic power in the sedated state. Many EEG complexity features and a few power features were highly predictive of a participant's recovery. These trends persisted after cross-validation, indicating they are reliable and may generalize to other epileptic patients. Rate entropy and HC-LMC had high predictive abilities, separating participants into recovered and non-recovered groups with 100% accuracy. These results suggest that rate entropy and HC-LMC are exceptionally indicative of an epileptic patient's capacity for consciousness and may serve as powerful prognostic tools in a PICU setting.

Even with dose randomization, we found good discriminative ability between low and high GOS-E. This result indicates that measuring EEG complexity under sedation, regardless of the sedative dose, can help predict patient recovery. However, the accuracy of the logistic regression was greater with a high sedative dose. Therefore, while any sedative infusion within the typical PICU dosage range has prognostic capabilities with EEG complexity analysis, higher sedative doses best predict recovery.

The complexity feature rate entropy is the time-resolved derivative of entropy, a measure of the amount of information, or uncertainty, contained in a signal[28]. We demonstrated that higher rates of change correlate to high GOS-E, indicating that greater changes in entropy are associated with better recovery. The brain reconfigures with injury; post-injury plasticity is a compensatory mechanism that aids recovery[29,30]. Epilepsy and neuroplasticity are fundamentally interconnected—epilepsy can induce plasticity, and the extent of neural reconfiguration influences epileptic progression[31,32]. Rate entropy may reflect the brain's ability to reorganize and adapt, serving as a proxy for epilepsy-induced neural plasticity. A brain with greater entropic changes after injury may be more resilient, modifying its activity patterns as an adaptive mechanism. High versatility and capacity for change may therefore underlie a patient's recovery of consciousness. These results suggest that measuring EEG changes in entropy in patients undergoing anesthesia can accurately predict their epileptic progression.

HC-LMC is a complexity feature that assesses the amount of structured patterns within a signal[33]. At low values of HC-LMC, a system is either highly ordered or disordered, whereas higher values yield a greater balance of order and disorder[34]. Interestingly, better recovery is correlated with lower values of HC-LMC—fewer structured patterns. Under anesthesia, neural complexity is lessened. Patients who maintained a balance of order and disorder under anesthesia had a lower capacity for consciousness, so the ability to sustain asymmetry of these measures with sedation may be crucial for recovery. Epilepsy induces bursts of brain activity and structured patterns in the signal, which are associated with higher HC-LMC. Therefore, participants with greater HC-LMC may have more epileptic activity and worse recovery. Although we demonstrated that HC-LMC has great potential to predict the recovery of consciousness, it is an understudied complexity feature in clinical contexts. These results highlight the need for future research to understand how HC-LMC reflects brain dynamics and to assess its utility as a predictive marker of clinical outcomes.

We demonstrated that rate entropy and HC-LMC can predict the recovery of epileptic pediatric patients in this cohort with 100% accuracy. These are not simple features of neural complexity, but intricate measures of the rate of entropic change and the balance of order and disorder. Accordingly, higher complexity is not always associated with better recovery—we observed a negative trend between GOS-E and HC-LMC. Our results demonstrate that EEG features under sedation can reveal a patient's capacity for consciousness, building on current findings. The high accuracy of the logistic regression highlights EEG as a powerful and accessible tool to predict epilepsy outcomes. EEG markers of consciousness, such as rate entropy and HC-LMC, could enhance clinical decision-making and improve our understanding of the neural mechanisms underlying recovery.

Limitations and Future Directions

While the results suggest that rate entropy and HC-LMC have strong prognostic ability, these conclusions are limited by the small sample size. We tested 12 participants; more work is needed to verify if the observed trends generalize to larger samples. Further, we had unbalanced groups: 5 participants with low GOS-E and 7 participants with high GOS-E. We had no participants with a GOS-E score of 2, 5, or 6. To substantiate these findings, our results should be validated with a greater diversity of GOS-E scores, particularly in the worse recovery group.

We showed that rate entropy and HC-LMC are powerful markers in the prognosis of epileptic pediatric patients. Future studies could investigate these markers in other etiologies—are they specific to epilepsy, or do they predict recovery in different conditions? Further, it would be valuable to explore these EEG features in a healthy control pediatric sample. These results could serve as a baseline for evaluating a patient's degree of altered neural activity.

Conclusion

We established rate entropy and HC-LMC as accurate and valuable EEG complexity features for predicting recovery in epileptic pediatric patients in the PICU. These features give insight into dynamic changes in entropy and the brain's intricate balance between order and disorder. Our findings reveal that the sedated state is the most predictive of recovery, highlighting the prognostic value of EEG analysis under anesthesia. Rate entropy and HC-LMC are clinically relevant features that perfectly classify recovery outcomes. They may reflect fundamental neural mechanisms, such as plasticity and adaptability, that are crucial for a patient's capacity for consciousness. The integration of these features into clinical decision-making could advance accessible prognostication, offering clinicians effective and accurate tools to assess recovery in epileptic patients.

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Supplementary Material

Supplementary material referenced in the text of this article may be found online at https://doi.org/10.26443/msurj.v1i1.288.

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