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Frontal long-range temporal correlations as a predictor of child's IQ test performance using machine learning approach

Alexander K. Kuc[a]

Immanuel Kant Baltic Federal University, A. Nevskogo Str. 14, Kaliningrad 236016, Russia

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Abstract This study explores the relationship between long-range temporal correlations in brain activity, measured through detrended fluctuation analysis of electroencephalogram signals, and performance on an intelligence test (Raven's Progressive Matrices) in children. Specifically, the research focuses on identifying reliable neurophysiological markers of cognitive functions by analysing EEG data from school-aged children (8–10 years old) in a resting state. The DFA scaling factor in the alpha range of the frontal cortex was found to be a significant predictor of RPM performance, with results validated using machine learning methods. These results highlight the importance of long-range temporal correlations in brain activity as a potential neurophysiological marker for assessing cognitive abilities.

1 Introduction

Problem overview. Intelligence is a complex and multifaceted cognitive function that affects the ability to learn, socialise and adapt [1]. Intelligence plays a key role in cognitive development, which is viewed as a process of skill acquisition that depends on the interaction of a variety of factors [2]. Assessment of intelligence is important not only in determining children's performance at school [3], but also in predicting their success in later life. The research shows that higher cognitive abilities contribute to better adaptation to the educational process, learning new knowledge and skills, and preparation for future professional activities [4].

To track the dynamics of cognitive development, it becomes necessary to regularly assess the level of intelligence [5]. Frequent assessment allows to adjust developmental programmes and adapt educational methods to individual needs [6], which is especially important for children, as this is the period when the foundations of their intellectual growth are being laid [7].

By far the most common methods for assessing intelligence and cognitive ability are standardised tests and questionnaires [8]. Despite their prevalence, such methods have drawbacks that may reduce their accuracy and reliability.

First, as demonstrated by Clark and Maguiri's study, questionnaires may not always capture the reported cognitive functions in sufficient detail, which can lead to scoring errors [9, 10]. Second, traditional methods are prone to the learning effect of repeated testing. As demonstrated by Faletti and colleagues, administering repeated tests can lead to higher scores without a corresponding improvement in cognitive function [11]. This phenomenon can lead to distorted data regarding cognitive changes. Such effects make regular diagnosis difficult and make it challenging to monitor cognitive change over time, which is particularly important in the context of early learning and prevention [12, 13]. These problems emphasise the need for more reliable assessment methods that are not influenced by mentioned effects and external factors. In addition, existing questionnaires often assume a specific educational and cultural context, making them difficult to apply to children with different educational and cultural backgrounds [14].

The development of machine learning (ML) and neurophysiological data analysis has opened new opportunities for objective assessment of cognitive functions. For example, ML algorithms are now being used for early detection of cognitive impairment based on cognitive abilities and neuroimaging data [15]. However, much of these algorithms

[a] e-mail: kuc1995@mail.ru (corresponding author)

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still rely on test results and questionnaires to categorise levels of cognitive function, which exacerbates the problems associated with the subjectivity of assessment.

This emphasises the need to develop new objective methods of cognitive assessment that can be used in conjunction with existing subjective approaches, thereby increasing diagnostic accuracy and promoting the development of neuroadaptive systems aimed at improving students' cognitive abilities [16].

Electroencephalography (EEG) offers unique opportunities to address this issues. For decades, this method has been actively used to study the dependence between brain activity and cognitive abilities. Classical studies such as a work of Gasser et al. [17] have demonstrated that EEG parameters such as frequency peaks and spectral characteristics have significant positive correlations with IQ, especially in children with mental retardation. The use of computerised data analysis has made it possible to identify patterns of brain activity associated with higher cognitive performance, which opens new perspectives for assessing and monitoring intelligence.

In subsequent years, the focus of research shifted to the study of coherence and phase delay. Thatcher et al. [18] showed that a decrease in phase delay and synchronisation of processes in the frontal lobes of the brain are associated with high IQ. These results emphasise the significance of the analysis of neuronal synchronisation as a key mechanism of cognitive performance.

In parallel, special attention was paid to EEG alpha rhythms. Doppelmayr et al. [19] found that the power of alpha rhythms in the upper range is positively correlated with semantic memory and intelligence, supporting the "neural efficiency" hypothesis, according to which more intellectually developed people demonstrate more economical use of brain resources. Interestingly, different sub-ranges of the alpha rhythm have different dependences with cognitive processes: the upper alpha range correlates better with semantic memory, whereas the lower ranges are related to learning and attention. This indicates the multi-layered nature of the interactions between brain rhythms and intelligence.

Additionally, Anokhin and Vogel [20] focussed on alpha rhythm frequencies and their relationship to verbal cognitive abilities. They showed that people with a higher frequency of alpha rhythm in the frontal lobes have improved abilities in solving verbal tasks.

Modern approaches emphasise information flows in the brain. A study by Luo et al. [21] demonstrated that the intensity of information flows, measured through the phase slope index, correlates with IQ, indicating the role of effective functional connectivity in cognitive performance.

Thus, the use of EEG provides a deeper understanding of the complex mechanisms underlying intelligence and offers promising solutions for the development of objective methods for assessing cognitive functions. A promising approach is the use of neurophysiological biomarkers combined with ML approaches [22], which offer opportunities for objective assessment of cognitive function and are not influenced by external factors [23].

Contribution of the study. The objective of this study is to identify reliable and objective predictors of child cognitive function based on the results of the Raven's progressive matrices (RPM) test, a widely recognised nonverbal measure of fluid intelligence. The RPM test assesses problem-solving and abstract reasoning skills, which are critical for learning and adaptation.

This study investigates the potential of using brain electrical activity signals as biomarkers for predicting IQ obtained during the RPM test. In particular, we analyse EEG data using the detrended fluctuation analysis (DFA) method to investigate the presence of long-range temporal correlations between time series [24]. In the field of brain research, the DFA method has been applied specifically to EEG signals with the objective of studying the complexity and dynamics of brain activity [25, 26]. The analysis of the DFA scaling factor calculated for EEG signals allows researchers to gain insight into cognitive processes, neural efficiency and the basic mechanisms of brain function. Furthermore, the DFA method has been demonstrated to be a valuable tool in the investigation of neurological disorders and their impact on brain activity [27–31]. However, there is currently no clear understanding of the relationship of the DFA scale factor to traditional brain activity metrics, such as phase synchronisation between brain regions.

Therefore, in this study, we have formulated two hypotheses that we intend to test. (i) The first hypothesis aims to determine whether DFA scaling factor can be used as a reliable predictor of IQ level in schoolchildren obtained during the RPM test.. We aim to investigate the potential relationship between the DFA scaling factor, which is a measure of long-range temporal correlations in time series of brain activity, and participants' IQ scores. (ii) The second hypothesis aims to investigate the correlations between the DFA scaling factor and EEG network metrics. By investigating these correlations, we can gain insight into the relationship between the complexity of brain activity, as reflected by the DFA scaling factor, and functional brain networks.

Thus, the novelty of the work consists in applying the DFA method to analyse children's cognitive abilities, and in investigating the links between this parameter and metrics of functional brain connectivity.

The study design is presented in Fig. 1. First, we consider an experimental dataset consisting of raw EEG recordings from schoolchildren aged 8–10 years old at rest. We perform basic preprocessing, including bandpass and notch filtering, and removal of eye-movement and muscle artefacts using independent component analysis.

Second, the data are processed using two different approaches: phase coherence between EEG channels and detrended fluctuation analysis. As a result, the following characteristics are obtained: within-regional phase-locking value (PLV), between-regional PLV and DFA scaling factor.

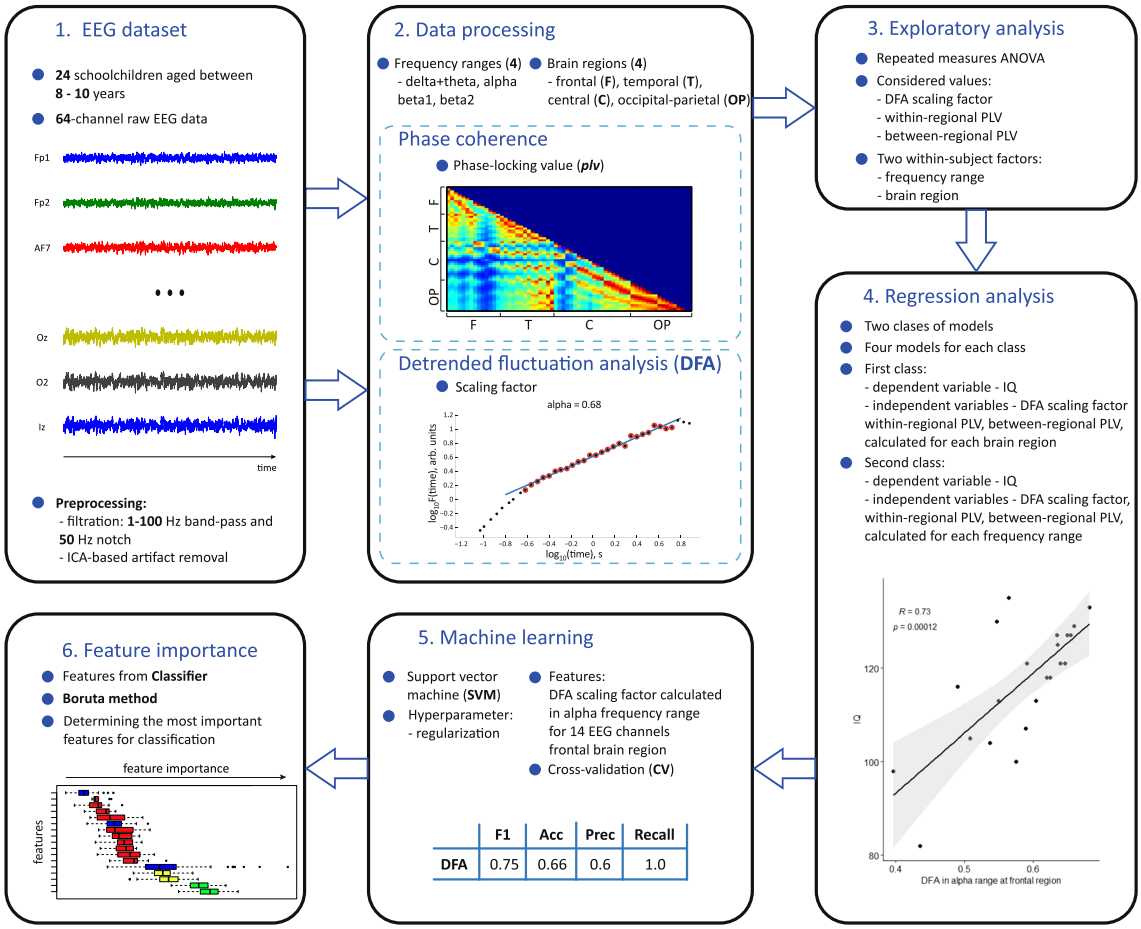

Fig. 1 Structure of the study. Block 1: Experimental EEG recordings of 8–10 year old schoolchildren. The insets show examples of raw EEG data as well as the preprocessing pipeline. Block 2: We consider two different approaches for data processing: phase coherence variation and detrended fluctuation analysis. The corresponding subplots schematically show the processing results of each method. Block 3: exploratory data analysis is used to identify main statistical effects. Block 4: Regression analysis is used to identify the frequency range and brain regions that contribute meaningfully to IQ prediction. The subplot shows the relationship between the scaling factor of the DFA scaling factor in alpha range at frontal region and IQ. Block 5: The result of training the classifier using support vector machine (SVM) method. The classifier is trained on the features identified using regression analysis. The table shows the performance of the classifier. Block 6: The importance of features is ranked using Boruta's method. Here is an example of ranking the importance of features

Third, we used the exploratory analysis of the obtained values of the DFA scaling factor, within-regional PLV and between-regional PLV to identify main statistical effects.

Fourth, using regression analysis, we test the ability to predict IQ based on the obtained characteristics. In addition, we identify the frequency range and brain region that contribute meaningfully to the prediction of IQ level.

Fifth, we apply the ML approach to classify subjects according to intelligence level. We train an support vector machine (SVM)-based classifier on the features identified by regression analysis. Our results show high classification accuracy ($F1$-score $= 0.75$).

Sixth, we identify the features most important for classification using Boruta's method. We observe that only right frontal EEG channels are significant for classification.

2 Methods

2.1 Participants

A total of 24 schoolchildren (10 girls and 14 boys aged between 8 and 10 years) participated in the study. All the children attended the same school and were in the third or fourth grade. All participants were conditionally healthy with no history of medical brain conditions. None of the subjects had previously participated in similar studies.

All subjects participated in the experiment of their own volition, but only after obtaining the approval of their parents. Parents were provided with comprehensive information regarding the aims and methodology of the study, and were afforded the opportunity to inquire about any aspects of the study that they deemed pertinent. They were also given detailed responses to their queries. In this manner, parents were furnished with all the requisite information to determine whether they endorsed their child's involvement in the study. Thereafter, the parents signed informed consent.

This study was conducted in accordance with the tenets set forth in the Declaration of Helsinki and was approved by the Ethics Committee of Immanuel Kant Baltic Federal University (Protocol No. 32 of 04.07.2022).

2.2 Experimental procedure

The experimental study was comprised of two distinct components: an assessment of the subject's performance on Raven's progressive matrices (RPM) and a two-minute EEG recording conducted in a resting state.

The RPM is a non-verbal test that is commonly used to measure an individual's general intelligence and abstract thinking abilities [32]. Additionally, RPM is regarded as a means of evaluating fluid intelligence [33]. Fluid intelligence is frequently linked to the capacity to resolve novel logical challenges, which in turn is associated with a number of key abilities, including comprehension, problem-solving and learning [34].

The RPM test comprises 60 multiple-choice questions, distributed across five sets of increasing difficulty. Each item is presented as a visual stimulus, comprising a pattern of dots, lines, and shapes, with a missing part (see example in Fig. 2). The objective for the test taker is to complete the image by selecting the option that best fits the blank space. The results of the RPM are converted into an intelligence quotient (IQ) according to the age of the test taker.

In the present study, the participants completed the RPM in standard format with pen and paper.

To reduce the potential stressors associated with the experimental procedure, we conducted EEG recordings in a setting that was familiar to the subjects. Furthermore, we also used a mobile EEG recorder instead of a stationary one to avoid limiting the participants' movement. The EEG recordings were conducted at the educational facility in the morning in a room with natural light and minimal external stimuli. Wherever possible, external stimuli such

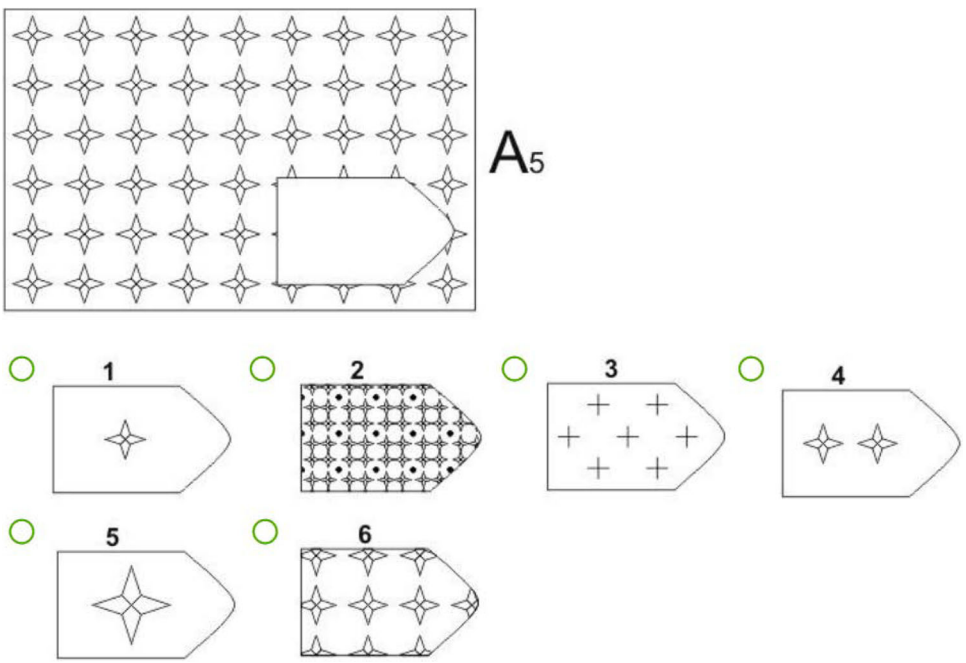

Fig. 2 Example of task in Raven's progressive matrices

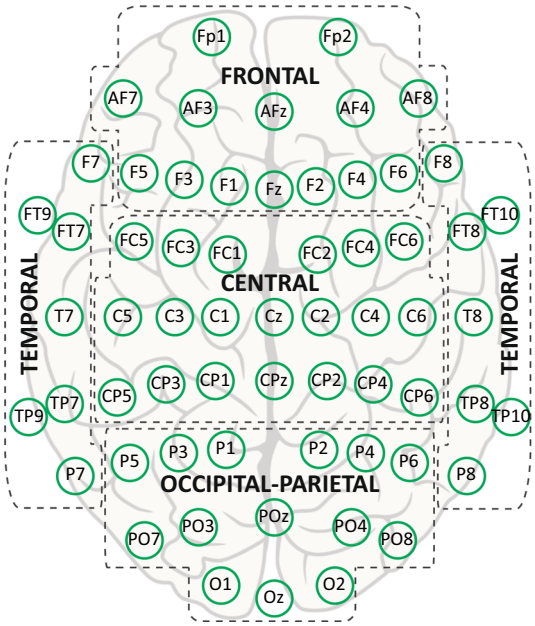

Fig. 3 Scheme of EEG channel segmentation into four zones: frontal, central, occipital-parietal and temporal

as loud sounds and bright lights were minimised. During the recording the subject was sitting in a comfortable chair. The subject was instructed to remain relaxed, seated and with their eyes open.

Furthermore, the educational success of the experimental participants was evaluated by considering their average grades in all subjects studied during the school year. The subjects included: Mathematics, Native language (Russian), Literature, Foreign language (English), Biology, Physical education, Music, Art, and Technology.

2.3 EEG recording and preprocessing

EEG signals were recorded using "LiveAmp" device (Brain Products, Germany) with Ag/AgCl ActiCap active electrodes. A total of 64 channels were recorded in accordance with the "10-10" system, with ground and reference electrodes positioned at the "Fpz" and "Fz" positions, respectively. Prior to the commencement of data acquisition, the scalp was treated with "NuPrep" abrasive gel to enhance skin conductivity. Additionally, "SuperVisc" conductive gel was applied during electrode placement to attain optimal impedance values. Prior to the commencement of the experiment, the impedances were verified to ensure that the desired value of $< 25\,\mathrm{k}\Omega$ was achieved.

The EEG signals were recorded at a sampling rate of 1000 Hz and subsequently processed with filters, namely a bandpass filter with cut-off points of 1 Hz and 100 Hz, and a 50-Hz notch filter. Physiological artefacts related to heart rate and eye movements were removed using independent component analysis (ICA) [35]. The implementation of ICA was conducted using the Fieldtrip toolbox for MATLAB [36]. The EEG dataset comprising 64 channels was decomposed into 64 independent components. Subsequently, components exhibiting artefacts were identified and removed, after which the EEG signals were reconstructed.

The neural activity of the brain was analysed at rest over a period of 120 s in four frequency ranges, which correspond to the main brain rhythms: theta- and delta-bands (1–7 Hz), which reflect low-frequency activity; alpha-band (6–13 Hz); beta1-band (13–20 Hz) and beta2-band (20–30 Hz). The recording electrodes were grouped into four zones: frontal (Fp1, Fp2, AF7, AF3, AFz, AF4, AF8, F5, F3, F1, Fz, F2, F4, F6), central (FC5, FC3, FC1, FC2, FC4, FC6, C5, C3, C1, Cz, C2, C4, C6, CP5, CP3, CP1, CPz, CP2, CP4, CP6), occipital-parietal (P5, P3, P1, P2, P4, P6, PO7, PO3, POz, PO4, PO8, O1, Oz, O2) and temporal (F7, F8, FT9, FT7, FT8, FT10, T7, T8, TP9, TP7, TP8, TP10, P7, P8). The chosen zones are illustrated in Fig. 3.

2.4 Detrended fluctuation analysis

Long-range temporal correlations were estimated utilising the DFA method [37]. DFA represents a variant of mean-square random walk analysis, entailing the fitting of a slow nonstationary component, conceived as a trend, with the subsequent characterisation of fluctuations around the signal profile, including deviations from the trend.

The DFA was calculated in the four frequency ranges $[f_1, f_2]$ considered in Sect. 2.3. For each frequency ranges, the DFA was calculated for each channel ($i = 1, \ldots, C; C = 64$).

The calculation of the DFA for each i-th channel of the EEG $X_i(t)$ includes the following steps.

1. **Filtering the signal $X_i(t)$ in the frequency range** $[f_1, f_2]$. We used a finite impulse response (FIR) filter whose order was set to $2/f_1$ s, where f_1 is a lower frequency of analysed frequency range. Thus, we can guarantee that the filter window will cover at least two cycles of oscillations with frequency f_1 Hz.
2. **Calculation of the amplitude envelope using the Hilbert transform**. The envelope amplitude of the EEG signal was used for further analysis, as it allows us to investigate slow dynamic patterns of neural activity related to cognitive functions and brain state [31, 38, 39]. This makes the analysis more informative and physiologically meaningful. A Hilbert transform $\hat{X}_i(t)$ is performed on the filtered signal $X_{i,[f_1,f_2]}(t)$ to produce a phase-shifted signal [40]:

$$X_i(t) = \frac{1}{pi}\int_{-\infty}^{\infty}\frac{X_{i,[f_1,f_2]}(\tau)}{t-\tau}\mathrm{d}\tau. \tag{1}$$

   The analytic signal $Z_i(t)$ is obtained as the sum of the original signal and its Hilbert transform: $Z_i(t) = X_{i,[f_1,f_2]}(t) + j\hat{X}_i(t)$, where j is an imaginary unit. The envelope amplitude is defined as a modulus of the analytic signal:

$$A_i(t) = |Z_i(t)| = \sqrt{X_{i,[f_1,f_2]}(t)^2 + \hat{X}_i(t)^2}. \tag{2}$$

3. **Construct of a cumulative series**. In the initial stage of the process, a cumulative series, designated as $Y_i(k)$, is constructed using the envelope amplitude $A_i(t)$ of length N:

$$Y_i(k) = \sum_{t=1}^{k}[A_i(t) - \bar{A}_i], \tag{3}$$

   where $\bar{A}_i = \frac{1}{N}\sum_{t=1}^{N} A_i(t)$, k is the ordinal number of the element in the time series for which all previous values of $A_i(t)$ from 1 to k are summarised.
4. **The data set is divided into discrete segments**. The cumulative series is partitioned into $N_s = N/s$ segments of length s, with an overlap of 50%.
5. **Removal the trend observed in each segment**. A polynomial regression is performed at each segment of length s. The resulting trend, $Y_i^s(k)$, is then subtracted from the cumulative series, thereby obtaining "decorrelated" fluctuations:

$$F_i^2(s, \upsilon) = \frac{1}{s}\sum_{k=1}^{s}(Y_i[(\upsilon-1)s + k] - Y_i^s(k))^2, \tag{4}$$

   where $\upsilon = 1, 2, \ldots, N_s$ is the index of the segment.
6. **RMS fluctuation**. The root-mean-square (RMS) fluctuation is calculated for each and every segment:

$$F_i(s) = \sqrt{\frac{1}{N_s}\sum_{\upsilon=1}^{N_s} F_i^2(s, \upsilon)}. \tag{5}$$

7. **Repetition for different scales**. Steps 3–5 are repeated for varying for values of s, which correspond to different scales.
8. **The construction of the dependence and estimation of the scale factor**. Plot the fluctuation function $F_i(s)$ for all segment sizes, s, on logarithmic axes. The DFA scale factor, α, is the slope of the trend line in the selected range of s and can be estimated using linear fitting.

The detrended fluctuation analysis were performed using the Neurophysiological Biomarker Toolbox [41]. The fluctuations were calculated in each frequency band, using h = 50% overlapping windows from 0.8 to 30 s, and the DFA exponent was found by fitting from 2 to 15 s. For each subject, we averaged the DFA exponents over the regions of interest.

2.5 Phase coherence

We used phase-locking value (PLV) to estimate phase coherence between the pair of EEG signals [42]. First, we filtered the signal in the frequency ranges of interest using a FIR filter. Second, we segmented the 30-s recordings

into the trials with the 50% overlap. The trials length depended on the frequency range of interest: 1250 ms (for 1–7 Hz), 500 ms (6–13 Hz), 312.5 (13–20 Hz) and 200 ms (20–30 Hz). We estimated PLV for each trial and averaged them across all trials. Finally, PLVs were averaged over the pair of sensors belonging to the same region of interest reflecting within-regional phase coherence. Similarly, we averaged PLVs across the channels pairs belonging to different brain regions, obtaining between-regional coherence.

2.6 Statistical analysis

The exploratory analysis of the obtained DFA scale factor, within-regional PLV and between-regional PLV values was conducted using repeated measures ANOVA, incorporating two within-subject factors: frequency range and brain region.

The relationship between brain activity parameters and cognitive characteristics of the subjects was analysed using linear regression and correlation analysis methods. The effect of the independent variables on the dependent variable was analysed using linear regression. The dependent variable was IQ, while the independent variables were the DFA scale factors, within-regional PLV and between-regional PLV calculated in all frequency bands and brain regions of interest, resulting in a total of 16 values for each brain activity parameters. Given the restricted sample size, it was not feasible to incorporate all 16 values into a single model. In lieu of this, two classes of models were trained, each comprising four models and four variables. In the first class, distinct models were constructed for each frequency range, with brain region included as a variable. In the second class, separate models were trained for each region, with the frequency range included as a variable. Models were fitted separately for values of the DFA scaling factor, within-regional PLV and between-regional PLV. A total of eight models were fitted for each brain activity parameters, with the significance level adjusted to 0.00625 due to multiple comparisons.

Correlation analyses were conducted to ascertain any linear relationships between neurophysiological parameters and cognitive performance. The relationship between the parameters was assessed using Pearson's correlation coefficient. The level of statistical significance was set at 0.05.

All calculations were conducted using the R software [43].

2.7 ML-based classifier

An ML-based approach was employed for the purpose of classifying subjects according to their respective intelligence levels. For this purpose, the subjects were divided into two groups based on the median IQ levels ($M = 119.5$). Those subjects whose IQ scores were below the median were categorised as *lowIQ*, while those whose IQ scores were above the median were categorised as *highIQ*. The DFA scaling factor calculated on the EEG channels belonging to the frontal brain region (14 features in total) were employed for the purpose of training the classifier.

A SVM classifier with the linear kernel was employed for the purpose of training. This method has been demonstrated to be an effective instrument for of analysing of EEG data, including the classification of various cognitive states [44–47]. The linear SVM operates by defining an optimal hyperplane that maximises the separation between two classes in the feature space, thereby increasing the gap between the data of each class. This approach enhances the model's resilience to noise and augments its capacity for generalisation. The regularisation parameter, denoted as R, is a hyperparameter that serves to adjust the balance between increasing the gap and minimising the classification error, thereby preventing overtraining. In order to optimise this parameter, the GridSearch method was employed in order to maximise the F1-score [48].

The performance of the ML-based model was evaluated using k-fold cross-validation. The data from all subjects within the same group (lowIQ or highIQ) were partitioned into $k = 5$ subsets. The model was trained on $k - 1$ subsets and evaluated on the remaining subset.

To evaluate the quality of the ML model, the following metrics were calculated based on the number of true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN): accuracy, recall, precision and $F1$-score.

The Boruta method [49] was employed for the purpose of identifying the most significant features for classification. This method is based on a comparison of the original features with their corresponding "shadow features", which are generated by randomly permuting the values of the original features. The features exhibiting minimal discrepancy with their shadow counterparts are deemed inconsequential with respect to the predictive performance of the model.

3 Results

Results of the statistical analysis. We tested how the DFA scale factor depends on frequency range and brain region. A repeated measures ANOVA was conducted, with two within-subject factors: frequency range and brain

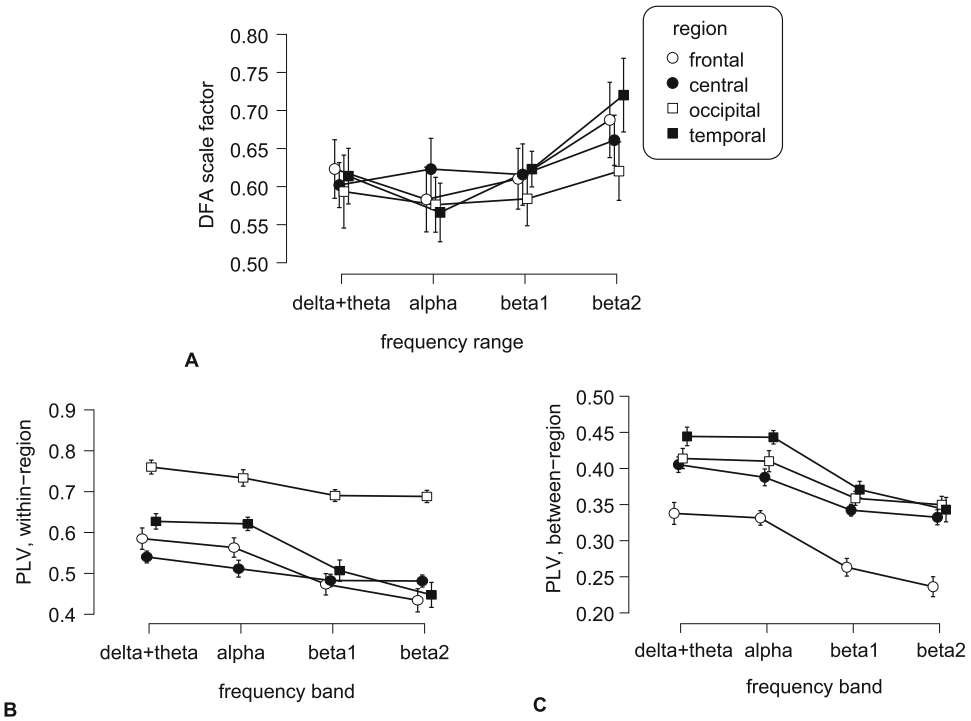

Fig. 4 The values of the DFA scale factor (**A**), within-region PLV (**B**) and between-region PLV (**C**) obtained for different regions and frequency ranges. Data are shown as group mean and 95% confidence interval

region (Fig. 4). The ANOVA analysis revealed a significant main effect of frequency range ($F(3, 63) = 7.889$, $p < 0.001$) and an interaction effect of frequency range and region ($F(9, 189) = 2.807$, $p = 0.004$). However, the main effect of region was not statistically significant ($F(3, 63) = 2.437$, $p = 0.073$). These findings suggest that the DFA scale factor exhibits variation across frequency ranges but remains consistent across brain regions. Furthermore, the variation in DFA scale factor across different frequency ranges is contingent on the specific brain region under consideration.

The post hoc analysis indicate that DFA scale factor in the beta2 range exceeds the DFA scale factor at the delta + theta range ($p = 0.005$, Holm correction), alpha range ($p < 0.001$, Holm correction) and beta1 range ($p = 0.005$, Holm correction).

The post hoc analysis of the interaction effect of frequency range and brain region indicate that in the frontal region, the DFA scale factor in the beta2 range is higher than that in the alpha range ($p = 0.007$, Holm correction). In the beta2 range, the DFA scale factor in the temporal region higher than that in the occipital region ($p = 0.003$, Holm correction). In the temporal region, the DFA scale factor in the beta2 range is higher than that in the alpha range ($p < 0.001$, Holm correction) and in the beta1 range ($p = 0.02$, Holm correction).

We tested how the within-region PLV depends on the frequency range and region. We used the repeated measure ANOVA with two within-subject factors: frequency range and region. The ANOVA revealed a significant main effect of the frequency range ($F(3, 63) = 168.642$, $p < 0.001$), region: ($F(3, 63) = 107.099$, $p < 0.001$), and an interaction effect of the frequency range and region ($F(9, 189) = 38.087$, $p < 0.001$). These results mean that the within-region PLV takes different values in different regions and frequency ranges. Moreover, the way how the within-region PLV varies across different regions depends on the frequency range.

These effects are illustrated in Fig. 4B. The post hoc analysis of the main effect of the frequency range reveals that within-region PLV in the beta2 range is lower than in the other ranges (all $p < 0.001$, Holm correction). In the beta1 range, within-region PLV is higher than in the beta2 range ($p < 0.001$, Holm correction), but lower than in the other two ranges (all $p < 0.001$, Holm correction). Similarly, in the alpha range, within-region PLV is higher than in the beta1 and beta2 ranges (all $p < 0.001$, Holm correction), but lower than in the delta + theta range ($p < 0.001$, Holm correction).

The post hoc analysis of the main effect of region reveals that within-region PLV in the occipital region is higher than PLV in the other regions (all $p < 0.001$, Holm correction). In the temporal region, within-region PLV is higher than in the frontal region ($p = 0.018$, Holm correction), and in the central region ($p = 0.003$, Holm correction). Finally, in the frontal region, within-region PLV does not differ from that in the central region ($p = 0.466$, Holm correction).

The post hoc analysis of the interaction effect of the frequency range and region reveals that in the beta2 range, frontal and temporal PLV do not differ ($p = 1.0$, Holm correction), and there is no difference between the frontal and central PLV ($p = 0.05$, Holm correction). Central and temporal PLV also demonstrate similar values

($p = 0.383$, Holm correction). In the beta1 range, there is no difference between frontal and central PLV ($p = 0.1$, Holm correction) as well as between frontal and temporal PLV ($p = 0.383$, Holm correction), and between central and temporal PLV ($p = 1.0$, Holm correction). In the alpha range, within-region PLV differs between the frontal and central regions ($p = 0.022$, Holm correction) as well as between frontal and temporal regions ($p = 0.006$, Holm correction). There is also a difference between the central and temporal regions ($p < 0.001$, Holm correction). Finally, in the low-frequency delta + theta range, within-region PLV does not change between the frontal and central regions ($p = 0.07$, Holm correction) as well as between frontal and temporal regions ($p = 0.112$, Holm correction). At the same time, there is a difference between the within-region PLV in central and temporal regions ($p < 0.001$, Holm correction).

We tested how the between-region PLV depends on the frequency range and region. We used a repeated measures ANOVA with two within-subject factors: frequency range and region. The ANOVA revealed a significant main effect of the frequency range ($F(3, 63) = 59.443$, $p < 0.001$), region ($F(3, 63) = 237.806$, $p < 0.001$), and an interaction effect of the frequency range and region ($F(9, 189) = 22.569$, $p < 0.001$). These results indicate that the between-region PLV takes different values in different regions and frequency ranges. Additionally, the variation of between-region PLV across different regions depends on the frequency range.

These effects are illustrated in Fig. 4C. The post hoc analysis of the main effect of the frequency range reveals that between-region PLV does not differ between the theta+delta and alpha ranges ($p = 0.36$, Holm correction). In the beta2 range, between-region PLV is significantly lower than in the beta1 range ($p = 0.04$, Holm correction). In turn, beta1 PLV is lower than the alpha range PLV ($p < 0.001$, Holm correction).

The post hoc analysis of the main effect of region reveals that in the frontal area, between-region PLV takes the lowest value compared to other regions (all $p < 0.001$, Holm correction). In the central region, between-region PLV is higher than in the frontal region ($p < 0.001$, Holm correction) but lower than in the other regions (all $p < 0.001$, Holm correction). In the occipital area, between-region PLV is lower than in the temporal region ($p < 0.001$, Holm correction) but higher than in the other three regions (all $p < 0.001$, Holm correction).

The post hoc analysis of the interaction effect of the frequency range and region reveals in the beta2 range, the between-region PLV in the central region exceeds PLV in the occipital region ($p = 0.034$, Holm correction) but does not differ from the PLV in the temporal region ($p = 0.874$, Holm correction). Finally, PLV does not differ between the temporal and occipital regions ($p = 1.0$, Holm correction). In the beta1 range, the between-region PLV in the central region takes a similar value as in the occipital region ($p = 0.056$, Holm correction) but differs from the PLV in the temporal region ($p < 0.001$, Holm correction). Similar to beta2, PLV does not differ between the temporal and occipital regions ($p = 0.534$, Holm correction). In the alpha range, the between-region PLV in the central region differs from the ones in occipital and temporal regions ($p < 0.001$, Holm correction). The between-region PLV also differs between occipital and temporal regions ($p < 0.001$, Holm correction). In the low-frequency delta + theta range, the between-region PLV is similar in the central and occipital regions ($p = 1.0$, Holm correction). At the same time, a significant difference is observed between the temporal and central regions ($p < 0.001$, Holm correction) as well as between the temporal and occipital regions ($p < 0.001$, Holm correction).

Finally, we tested whether the DFA scaling factor correlates with the PLV using Pearson's correlation. Since DFA and PLV depend on the frequency range and region, we performed correlation analysis separately for each combination of the frequency range and region. As a result, there was no correlation between DFA and PLVs for any frequency range in any region.

Regression analysis. Statistical analysis has provided us with detailed information about the dependence of various parameters of neurophysiological activity on frequency ranges and brain regions. We have shown that neurophysiological activity parameters vary across frequency ranges and brain regions. The identified statistical effects were further explored using regression models to understand in more detail their contribution to subjects cognitive abilities.

A linear regression analysis was conducted to ascertain whether DFA scaling factors or PLV can be employed as a predictor of IQ. Two classes of models were trained. In the first class, distinct models were developed for each frequency range, with the inclusion of brain region as a variable. In the second class, separate models were trained for each region, with the frequency range included as a variable.

The results of these models are presented in Tables 1 and 2, which include the R-squared (R^2) and p values to assess the degree of fit. In the case of models with p values below 0.00625 (adjusted), we have bolded the p-values and R^2 and included detailed information on the contribution of each variable, presenting the coefficient value (β) and p value. Variables with p values above 0.00625 (adjusted) have been presented as '–'.

There is consistency of results between the models in the two groups. In both classes, only DFA was found to be the significant predictor of IQ. When the brain region was considered as a model variable (Table 1), the results demonstrated that DFA scaling factor in the alpha range was a significant predictor of IQ ($R^2 = 0.62$, $p = 0.002$). Further analysis revealed that only frontal DFA scaling factor was a significant predictor ($\beta = 0.66$, $p = 0.002$). When the frequency range was considered as a model variable (Table 2), only frontal DFA scaling factor was found to be a significant predictor of IQ ($R^2 = 0.551$, $p = 0.006$). A detailed analysis revealed that only alpha range DFA scaling factor made a significant contribution to the prediction model ($\beta = 0.687$, $p = 0.006$).

Table 1 Summary of the regression models: IQ is outcome variable, separate models are trained for different frequency ranges, regions serve as model variables

	Frequency range	Overall fit of the regression model	Importance of the region			
			Frontal	Central	Occipital	Temporal
DFA exponent	delta + theta	$p = 0.524$, $R^2 = 0.163$	–	–	–	–
	alpha	**$p = 0.002$, $R^2 = 0.62$**	$p = 0.002$, $\beta = 0.66$	–	–	–
	beta1	$p = 0.433$, $R^2 = 0.191$	–	–	–	–
	beta2	$p = 0.982$, $R^2 = 0.022$	–	–	–	–
PLV, within-region	delta + theta	$p = 0.767$, $R^2 = 0.097$	–	–	–	–
	alpha	$p = 0.542$, $R^2 = 0.158$	–	–	–	–
	beta1	$p = 0.709$, $R^2 = 0.113$	–	–	–	–
	beta2	$p = 0.731$, $R^2 = 0.107$	–	–	–	–
PLV, between-region	delta + theta	$p = 0.692$, $R^2 = 0.117$	–	–	–	–
	alpha	$p = 0.372$, $R^2 = 0.211$	–	–	–	–
	beta1	$p = 0.333$, $R^2 = 0.225$	–	–	–	–
	beta2	$p = 0.401$, $R^2 = 0.202$	–	–	–	–

Table displays uncorrected p values, while the significance level is set to 0.00625. In the case of models with p values below significance level, the p value and R^2 were bolded

Based on these results, we conclude that frontal DFA scaling factor in the alpha range is a reliable predictor of IQ. Figure 5A illustrates the relationship between frontal alpha range DFA scaling factor and IQ. Each subject's values are displayed along with the regression line (solid line) and 95% confidence interval (light grey area around the regression line). Furthermore, the Pearson correlation coefficient (r) between these variables is also presented. Furthermore, in order to examine the relationship between IQ and educational success, a correlation was conducted between IQ and average school grade (Fig. 5B). The results demonstrate a robust positive correlation between IQ and average grade: $r = 0.618$, $p = 0.002$, $95\%CI[0.265, 0.825]$.

Results of classification. Regression analysis revealed significant predictors of IQ level, in particular the DFA scale factor in the alpha range on the frontal region of the brain. These results were used to construct a classification model aimed at dividing subjects into high and low intelligence groups and building a reliable predictive model.

An SVM classifier was employed for the purpose of classifying subjects according to their respective intelligence levels. The classifier was trained on DFA scaling factor values calculated in the alpha frequency range for 14 EEG channels corresponding to the frontal brain region. The resulting classification metrics were as follows: Accuracy = 0.66, Precision = 0.6, Recall = 1.0, and $F1$-score = 0.75. The results are illustrated by the receiver operating characteristic (ROC curve) in Fig. 6. The figure shows the mean value for all folds, together with the standard deviation.

In order to ascertain the most important features for classification, Borut's method was employed. Figure 7 presents a box-plot diagram that ranks the features according to their importance (Panel A) and a topogram that visualises the most significant features (Panel B).

Figure 7A illustrates the distribution of the z-score, which is calculated as the ratio of the loss of classification accuracy due to random permutation of features to its standard deviation. The green box-plots illustrate the features identified as important by the algorithm, indicated by consistently higher z-scores than those of the shadow features. Red box-plots illustrate the features that were excluded on the basis of their lower z-scores in

Table 2 Summary of the regression models: IQ is outcome variable, separate models are trained for different regions, frequency regions serve as model variables

	Region	Overall fit of the regression model	Importance of the frequency range			
			delta + theta	alpha	beta1	beta2
DFA exponent	Frontal	**$p = 0.006$, $R^2 = 0.551$**	–	$p = 0.001$, $\beta = 0.687$	–	–
	Central	$p = 0.17$, $R^2 = 0.301$	–	–	–	–
	Occipital	$p = 0.9$, $R^2 = 0.058$	–	–	–	–
	Temporal	$p = 0.061$, $R^2 = 0.395$	–	–	–	–
PLV, within-region	Frontal	$p = 0.462$, $R^2 = 0.182$	–	–	–	–
	Central	$p = 0.586$, $R^2 = 0.146$	–	–	-	–
	Occipital	$p = 0.765$, $R^2 = 0.098$	–	–	–	–
	Temporal	$p = 0.718$, $R^2 = 0.11$	–	–	–	–
PLV, between-region	Frontal	$p = 0.95$, $R^2 = 0.039$	–	–	–	–
	Central	$p = 0.734$, $R^2 = 0.106$	–	–	–	–
	Occipital	$p = 0.936$, $R^2 = 0.045$	–	–	–	–
	Temporal	$p = 0.919$, $R^2 = 0.051$	–	–	–	–

Table displays uncorrected p values, while the significance level is set to 0.00625. In the case of models with p values below significance level, the p value and R^2 were bolded

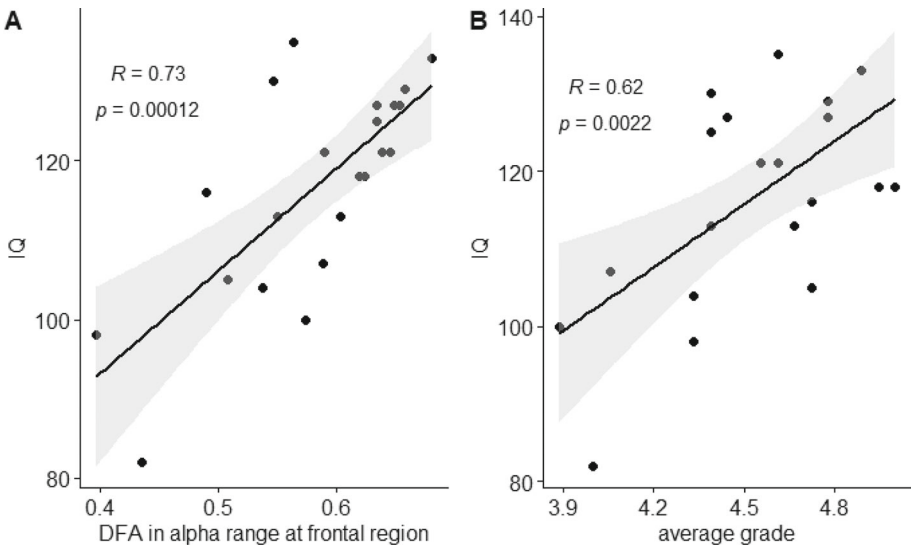

Fig. 5 Correlation between IQ and DFA (**A**) and between IQ and average grade (**B**). Data are shown as individual values (dots), regression line (solid), and 95%-confidence interval (light grey area around the regression line). Legend displays uncorrected p values, while the significance level is set to 0.003125

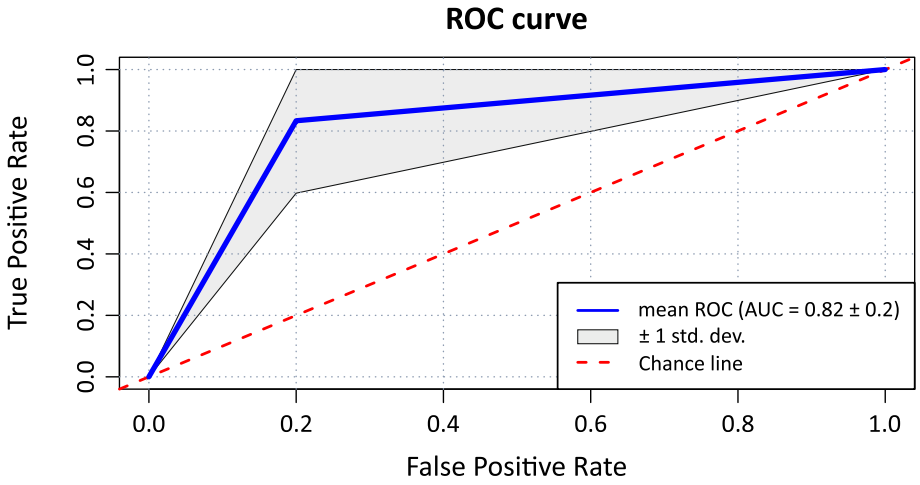

Fig. 6 Receiver operating characteristic (ROC-curve) for SVM classifier

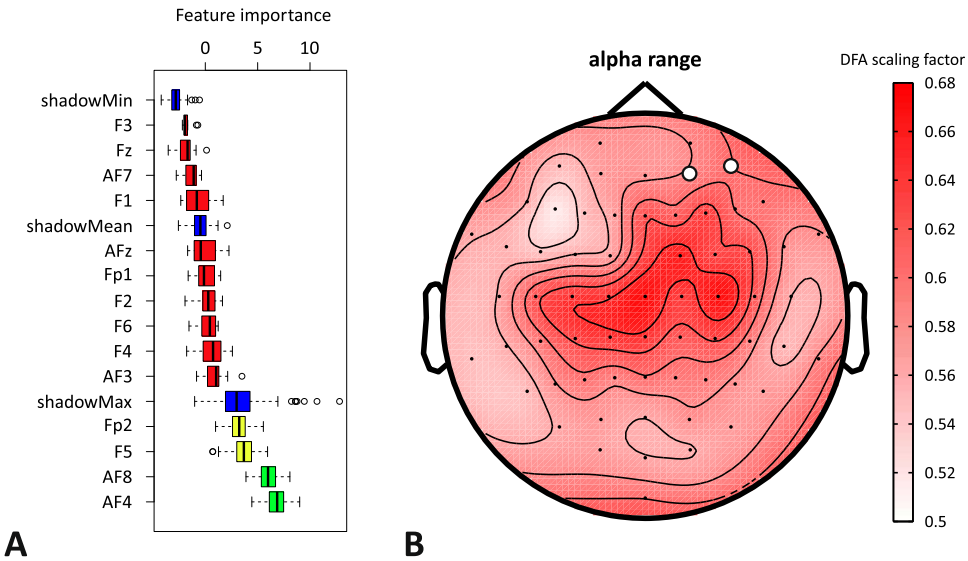

Fig. 7 Feature significance assessed with the Boruta method: **A** all features ranked by importance; **B** visualisation of the most important features on the head surface

comparison to the shadow features. Blue box-plots are employed to indicate shadow features that were incorporated into the model for comparison with the real features. Yellow box-plots show those features whose z-scores lie on the border of significance.

Figure 7B illustrates a topogram projected on the head surface with the distribution of DFA scaling factor values by EEG channels. The white circles indicate the EEG channels that are most important for classification purposes.

4 Discussion

The findings of our study with a group of 8–10 year old schoolchildren indicated that IQ scores were a significant predictor of their academic performance, as evidenced by their average grade in school (Fig. 5B). Furthermore, our findings indicate that an index of long-range temporal correlations in the time series of brain neural activity, particularly the DFA index in the frontal region in the alpha frequency range, can serve as an reliable predictor of a child's IQ (Fig. 5A). This is confirmed by the results of classification subjects with high and low intelligence based on SVM (Fig. 6). Importantly, we also observed that measures of functional connectivity such as phase synchronisation did not show a significant correlation with IQ (Tables 1 and 2) or DFA score.

Relationship to other studies. The application of DFA method to EEG analysis in our study yielded novel insights into the neural dynamics underpinning cognitive processes. This method has previously been successfully employed for the analysis of the complexity and dynamics of neural activity in the brain [25, 26]. This method has

been widely applied in the field of medical diagnosis [27] and the study of neural dynamics in various neurological diseases [50]. Additionally, the DFA method has been employed to investigate more complex cognitive brain functions, including the correlation between activation changes in EEG and cognitive load [41, 51], and the correlation between the DFA scale factor and academic performance in physics tasks [52].

In addition, other studies have shown that biomarkers of resting brain activity can be used to predict IQ [53]. A substantial body of research has been dedicated to investigating the potential applications of fMRI in this context. For example, the recent study has demonstrated that fMRI biomarkers based on resting-state functional connectomes can predict key measures of intellectual ability [54]. Similarly, another study employed resting-state fMRI and identify a positive correlation between brain entropy and intelligence [55]. In relation to EEG biomarkers, a number of studies have highlighted the capacity of distinct power- and coherence-based measures to predict IQ. Similarly, as in our study, these other studies frequently highlight the significant impact of the frontal region on such predictive outcomes [18]. More recent work has employed more sophisticated measures, such as a magnitude of information flow between different sensors, an has reported an inverse relationship with IQ, particularly in the alpha and beta frequency ranges [56]. Table 3 presents a comparison of the results obtained with the available literature data.

Taken together, the results of the present study are supported by those of recent studies in several aspects. Firstly, it has been consistently demonstrated that IQ as measured by questionnaires is an important predictor of academic success and future academic achievement. Secondly, the utilisation the DFA methodology to quantify the temporal characteristics of neurophysiological signals has yielded insightful data pertaining to cognitive processes, including IQ, beyond what can be captured by traditional metrics such as phase synchronisation. In light of these findings, we propose that the DFA scaling factor derived from non-invasive recording of brain electrical activity may serve as a valuable biomarker for monitoring a child's IQ in the context of the educational process. By assessing the DFA scale factor, educators and researches can obtain supplementary data regarding a child's cognitive abilities, which can inform the implementation of personalised educational interventions and facilitate the development of an effective learning pathway.

Table 3 Comparison of IQ prediction results with existing literature data

Study	Intelligence measurement	Method	Neurophysiological measures	Results
Current study	Raven's progressive matrices (RPM)	Regression analysis; support vector machine (SVM)	DFA exponent (EEG)	$p = 0.002$, $R^2 = 0.62$; accuracy = 66%
Tong X. et al. [46]	Wechsler Intelligence Scale for Children Fifth Edition (WISC-V)	Connectome-based predictive modelling (CPM)	Brain connectome signatures (rsfMRI)	$r = 0.5573$, $p = 0.001$
Saxe G.N. et al. [47]	Wechsler Abbreviated Scale of Intelligence (WASI)	Regression analysis	Brain entropy (fMRI)	Bilateral anteriorfrontal lobes—$p = 0.002$, $R^2 = 0.011$; inferiortemporal lobe—$p < 0.001$, $R^2 = 0.015$; bilateral cerebellum—$p = 0.043$, $R^2 = 0.005$
Thatcher R.W. et al. [48]	Wechsler Intelligence Scale for Children revised (WISC-R)	Discriminant analysis	Absolute power, relative power, RP-ratios, amplitude asymmetry, coherence, absolute phase (EEG)	Accuracy = 92.81–97.14%
Thatcher R.W. et al. [49]	Wechsler Intelligence Scale for Children revised (WISC-R) and Wechsler Adult Intelligence Scale Revised (WAIS-R)	Discriminant analysis	Phase Slope Index (EEG)	Accuracy = 94%

The results of correlation analysis showed that there was no significant correlation between DFA and PLV. These results suggest that measures of long-range temporal correlations of DFA, which reflect the complexity of temporal dynamics of brain activity, are not directly related to measures of phase synchronisation between brain regions. This may indicate the independence of the different aspects of neural activity reflected by DFA and PLV, which requires further investigation to better understand their contribution to cognitive processes.

Practical relevance in personalised education. The findings of our study have significant practical implications for the implementation of personalised education systems. In recent years, there has been a growing focus on the development of methods aimed at tailoring educational programmes to the individual characteristics of each student. The advent of neurotechnologies and artificial intelligence has created new avenues for the personalisation of the learning process and the development of more flexible educational pathways [57]. The findings of our study demonstrate that frontal EEG indicators, such as a DFA scale factor, can serve as objective biomarkers of cognitive abilities, thereby enabling the development of novel approaches to monitoring children's cognitive development.

Individual differences in intelligence and cognitive ability are of paramount importance with regard to the question of learning success. As demonstrated by the research of Mayes and colleagues, IQ and neurophysiological assessments are significant predictors of academic achievement [58]. The results underscore the value of objective measurement of brain activity in enhancing the prediction of educational achievement. The combination of existing tests and questionnaires with biomarkers, such as DFA scale factor, will facilitate the development of more accurate systems of assessing students abilities, thereby enhancing the effectiveness of personalised learning.

Furthermore, the regular monitoring of children's cognitive state using neurophysiological methods, such as EEG, can be beneficial for the early diagnosis of cognitive deviations and the implementation of corrective measures within the learning process. For example, [59] describes a system for monitoring the educational process based on the analysis of EEG data, which allows for the automatic adjustment of the learning process in accordance with the cognitive state of students. Consequently, the incorporation of neural dynamics analysis techniques into educational frameworks presents a promising avenue for the development of adaptive training programmes that can be tailored in real-time based on empirical data.

Limitations. Despite the significance of the findings, our study is not without its shortcomings. First, the study sample was relatively small and comprised children within a single age range (8–10 years old). This restricts the applicability of the findings to other age groups and necessitates further investigation utilising more diverse samples. It has been demonstrated that there are considerable variations in intellectual ability according to age, as well as other factors such as the educational context and cultural ability [53]. It would be beneficial for future studies to include a wider age range in order to gain a deeper understanding of how neurodynamic measures change with age and how they may be related to different stages of cognitive development.

Secondly, the present study was conducted under resting state, which precludes an assessment of the dynamics of neural activity during cognitive task. It has been demonstrated that the cognitive load and performance of complex tasks can have a significant impact on EEG measures, such as coherence and phase delay [18]. Consequently, on order to gain a more comprehensive understanding of the relationship between intelligence and neural dynamics, it is essential to incorporate tasks that demand high levels of cognitive activity, such as working memory tasks, into the experimental design.

In addition, while our study demonstrates a significant association between the DFA scaling factor in the alpha band of the frontal cortex and IQ obtained from RPM tasks, it is important to acknowledge the limitations of these findings. RPM is a well-established test of fluid intelligence, specifically assessing abstract reasoning and problem-solving skills [32]. Consequently, the observed relationship between DFA and IQ obtained from RPM tasks should not be interpreted as evidence of a generalizable link between DFA metrics and overall intelligence or learning success.

Finally, we used only one method of EEG analysis, DFA. Although this method has been demonstrated to be an effective approach for examining long-range temporal correlations, alternative analytical techniques, such as coherence or spectral power, can also valuable insights into the neural dynamics of the brain. In particular, studies have demonstrated that EEG coherence can serve as a significant predictor of cognitive ability [56]. It would be beneficial in the future to consider utilising a combination of analytic techniques for a more comprehensive evaluation of brain activity.

5 Conclusion

Our results indicate that DFA scaling factor in the alpha band of the frontal cortex is associated with IQ test performance, suggesting its potential as a neurophysiological marker. The DFA scaling factor in the alpha band of the frontal cortex demonstrated the most pronounced association with IQ, which is consistent with previous studies that have emphasised the importance of frontal activity and alpha rhythms in cognitive processes. These findings

have significant implications for our understanding of the brain mechanisms associated with cognitive abilities and highlight the necessity for further investigation into the neurodynamic processes that underpin intelligence.

The combination of neural dynamics analysis techniques, such as DFA, with traditional psychological tests has the potential to facilitate a more personalised approach to education. The utilisation of objective neurophysiological biomarkers to monitor the cognitive state of children presents a potential avenue for the early diagnosis of possible developmental deviations and the adaptation of the educational process to the individual characteristics of each student. The introduction of such methods will facilitate a more accurate determination of the needs of students by schools and educators, as well as development of personalised curricula based on data on cognitive activity and intellectual abilities.

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Data availability The dataset presented in this study can be obtained on request.

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