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DISTANCE-BASED INTEGRATION OF ERP CORRELATION ANALYSIS

Abstract *Interpretation of cognitive performance is a paramount pursuit in learning achievements. Cognitive abilities, encompassing attention, memory, decision-making, and language comprehension, are recognized on individual's capacity to navigate in diverse cognitive tasks. In the academic domain, optimal cognitive functioning is essential for effective learning, information retention, and problem-solving. Proficiency in cognitive skills is directly linked to academic success and intellectual development, providing the necessary cognitive tools for processing, and synthesizing complex information. Therefore, this study explores the correlation between event-related potential (ERP) sub-components (P300, N170, N400) to assess the intricacies of cognitive performance. A regularized approach utilizing Spearman's Rank Correlation Coefficient and Euclidean Distance is employed. Positive correlations reveal consistent relationships among P300, N170, and N400 ranks across ERP waveforms, indicating similar response patterns. Negative correlations denote inverse relationships. Moreover, the theoretical framework focuses on the digital filtering, ensemble averaging, and baseline correction from data contrast discrimination tasks. Findings indicate positive correlations, suggesting higher ERP amplitudes correspond to superior cognitive performance. This tailored and integrated methodology, indicating the correlation between ERP sub-components, contributes to the broader field of neuroscience and informatics, potentially informing cognitive enhancement strategies in education and bio-medical analysis.*

Keywords Spearman's rank correlation coefficient, correlation analysis, Euclidean distance, cognitive performance, event-related potentials, ERP, P300, N170, N400

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1. Introduction

Cognitive performance, encompassing processes such as attention, memory, perception, and decision-making, is a fundamental aspect of human functioning. The brain's ability to process and interpret information is vital for problem-solving, learning, and decision-making, impacting academic and professional success, daily functioning, and overall quality of life. High cognitive performance facilitates efficient information processing, effective decision-making, rapid learning, and adaptation to changing environments. Conversely, cognitive impairment can hinder independence, social interactions, and daily tasks, particularly as individuals age. Research in assessing and enhancing cognitive performance has grown in importance, aiming to optimize brain function and promote cognitive well-being.

Event-Related Potentials (ERPs) are specific patterns of brain activity measured through electroencephalography (EEG) in response to sensory, cognitive, or motor events. These brain responses are time-locked to stimuli, allowing researchers to examine the timing and stages of cognitive processing. ERPs are characterized by distinct wave components such as P1, N1, P2, N2, P3 (P300), N400, and LPC, each associated with different cognitive functions like sensory processing, attention, memory, and language comprehension. The amplitude and latency of these components provide insights into the intensity and speed of cognitive processes. ERPs are essential for understanding cognitive performance as they reflect the brain's real-time processing of information. Variations in P300 amplitude and latency are key indicators of learning performance across tasks involving visual or auditory discrimination, semantic processing, and spatial navigation. Changes in coherence patterns reflect alterations in neural synchronization and information transfer, key elements in learning and memory processes.

The P300 is a positive peak in the ERP waveform occurring approximately 300 milliseconds after stimulus presentation, associated with cognitive processes like attention, memory, and decision-making. Detecting the P300 typically involves measuring brain activity during experiments where subjects are exposed to various stimuli, often using the oddball paradigm. P300 is widely studied concerning learning performance and is associated with working memory capacity and attentional control.

The N170 is an ERP sub-component elicited by faces and other visual stimuli, essential in face processing and social cognition. Its amplitude and latency can be influenced by factors like familiarity, attention, and expertise, indicating its sensitivity to changes in perceptual and cognitive processing during learning. Similarly, the N400, elicited by auditory stimuli, is associated with early auditory processing, including sound localization and discrimination. The N400's amplitude and latency can be modulated by factors such as stimulus complexity, attention, and expertise, suggesting its sensitivity to changes in auditory processing during learning. The N170 amplitude is linked to face recognition ability, and the N400 amplitude relates to semantic processing and language comprehension.

The correlations between these ERP sub-components and learning performance offer potential biomarkers for assessing cognitive abilities in educational and training contexts. By measuring the amplitudes and latencies of these ERP sub-components, researchers can investigate the cognitive processes involved in different tasks and stimuli. Clinically, ERPs are used to diagnose and monitor neurological and psychiatric conditions, providing valuable data on the effectiveness of cognitive training and rehabilitation programs. ERP sub-components like P300, N170, and N400 serve as valuable biomarkers for cognitive performance assessment and enable a deeper exploration of the neural mechanisms underpinning cognitive processes. Analyzing ERP components provides detailed insights into neural mechanisms underlying cognitive functions, making ERPs a powerful tool in both research and clinical contexts.

This study aims to investigate the correlations between P300, N170, and N400, which are ERPs associated with various aspects of cognitive performance. By analyzing the amplitudes and latencies of these ERP sub-components, the study seeks to provide insights into the neural mechanisms underlying cognitive processes related to attention, memory, perception, and decision-making. The goal is to utilize these ERP sub-components as biomarkers to assess cognitive abilities and enhance educational and training strategies, contributing to a better understanding of cognitive performance and its potential applications in optimizing brain function and cognitive well-being.

2. Literature review

Identifying human cognitive performance can be done through various methods, including classification by general process involved, regional brain functions, and hierarchical structure based on the complexity of operations. ERP measures the brain's response to specific stimuli [17, 18]. This allows investigators to explore a nearly infinite number of domains where it is of interest to understand the relative timing of neural events in a non-invasive method [11].

In ERP, the stimulus is presented multiple times to the participant, and the responses are measured. ERPs are created by averaging responses to standard and deviant stimuli separately. ERPs measure voltage changes in the brain that occur following the onset of specific stimuli or cues and provide a measure of the timing of the brain's communication or timing of information processing. It is extensively used in neuroscience, cognitive psychology, cognitive science, and psychophysiological research to measure cognitive performance. The amplitude, latency, and topography of the resulting positive and negative deflections are taken to index the underlying mental operations. ERPs provide a continuous measure of processing between a stimulus and a response, allowing us to determine which stage(s) are being affected by a specific experimental manipulation.

Additionally, ERP records brain processes on a millisecond scale, capturing neural activity related to both sensory and cognitive processes. It is used in experimental settings and is involved in language research [36]. ERP can be associated with sensory encoding, inhibitory responses, updating working memory, and highlighting the temporal unfolding of neural activity associated with different cognitive aspects of language comprehension and production [23]. Moreover, studies have estimated the test-retest reliability of ERP waves, with interclass correlation coefficients between first and second recordings being around 0.8 for amplitude and around 0.9 for the latency of the P3 NOGO waves, indicating the reliability of ERPs as measures of brain functioning [6, 24].

Classification by general process involves memory, attention, language, and executive functioning, while regional brain functions are derived from lesion studies and include the frontal lobe, temporal lobe, parietal lobe, hippocampus, or other structures [20, 21]. Cognitive ability domains can also be conceptualized in several ways, such as a hierarchical structure based on the complexity of operations, with basic sensory and perceptional operations being the least complex and reasoning and problem-solving being the most complex [14]. Tests of general cognitive ability are used to identify human cognitive performance. The most used cognitive tests usually take 15 minutes or less and include repeating lists of words or spelling words backward [31]. These tests are good predictors of job performance and training success for a wide variety of jobs. Processing speed is the strongest predictor of overall cognitive performance and is correlated with impairments in everyday functioning, with coding tasks showing the most significant impairment in schizophrenia. However, there are inconsistencies in the clinical and research literature, especially in broad domains that may include multiple component processes [39]. In addition, there is an issue with the intrinsic validity of cognitive domains in populations other than those with specific regional brain damage [4]. Contemporary circuit-based conceptions focus on the activation and interaction of these circuits. Current methods such as smartphone assessment and remote cognitive assessment are more convenient for longitudinal assessment and can measure preclinical AD-related changes in long-term associative memory across varied memory retention intervals [35].

Moreover, there are a variety of methods available for measuring cognitive performance, including gamified assessment, smartphone assessment, and assessments of GPS data and gait characteristics [35]. Smartphone assessment is useful in measuring preclinical AD-related changes in long-term associative memory but requires retention intervals of at least 3 days to be sufficiently sensitive to differences in recall and recognition performance in adults without diagnosed cognitive impairment. Gamified assessment has been found to reduce testing anxiety and increase task engagement and enjoyment without affecting performance and can provide better construct and ecological validity than simple laboratory-based tasks thanks to a more realistic context [26]. Assessment of GPS data and gait characteristics measured through wearable accelerometers have also been found to differentiate among dementia subtypes with moderate accuracy, while recent developments allow neuropathology associated with potential cognitive decline to be accurately detected from peripheral blood samples [28]. However, the accuracy of these methods can be affected by various factors such as device type, operating system, and Wi-Fi connection, as well as subtle differences in task design and the lack of interoperability between cognitive functioning metrics.

In conclusion, while there are a variety of methods available for measuring cognitive performance, researchers need to carefully consider the strengths and limitations of each method to accurately assess cognitive function. The application of correlation and distance analysis holds great promise in advancing our understanding of cognitive processes associated with various tasks. By adopting these methods, this study can gain valuable insights into the limitations of traditional techniques such as ERP. The existing methods highlighted the strengths and limitations of existing methods, emphasizing the need for alternative approaches to studying cognitive performance. In this study, Spearman's rank correlation coefficient offers a statistical measure to examine the relationships between cognitive performance measures and other variables, providing valuable insights into cognitive processes. On the other hand, Euclidean distance analysis enables the assessment of similarity or dissimilarity in cognitive profiles, paving the way for future research and the development of diagnostic tools for cognitive impairments. By leveraging these methods, this study can further our understanding of cognitive processes, improve diagnostic accuracy, and enhance clinical interventions for individuals with cognitive impairments.

In summary, the research aims to employ correlation and distance analysis techniques to gain a deeper understanding of cognitive performance, bypassing the limitations of traditional methods like ERP. The study aims to explore relationships between cognitive performance measures and other variables using Spearman's rank correlation coefficient. Additionally, it seeks to assess the similarity or dissimilarity in cognitive profiles through Euclidean Distance analysis. Nevertheless, these methods can contribute to a more comprehensive understanding of cognitive processes and have the potential to enhance diagnostic accuracy and clinical interventions for individuals with cognitive impairments.

3. Theoretical framework

3.1. Cognitive performance and related ERP sub-components

Cognitive performance denotes an individual's capacity to process and utilize information, encompassing a spectrum of skills, including attention, memory, decision-making, problem-solving, and language comprehension effectively and efficiently. The evaluation of cognitive performance involves a diverse array of methods, spanning behavioral assessments, neuroimaging modalities, and electrophysiological measures, event-related potentials (ERPs) [37]. ERPs provide insights into the brain's electrical activity concerning specific events or stimuli. Among these ERPs, the P300, N170, and N400 stand as prominent sub-components frequently employed in the investigation of cognitive performance.

The P300, or P3 wave, manifests as a positive ERP sub-component, surfacing approximately 300 ms post-presentation of a target stimulus [29]. It is conventionally associated with cognitive processes such as attention, working memory, and decision-making. The amplitude and latency of the P300 serve as indicators of cognitive performance, with larger and faster P300 responses signifying enhanced cognitive processing and performance.

In contrast, the N170, a negative ERP sub-component, emerges approximately 170 ms following the introduction of a visual stimulus, typically a facial image [16]. Its primary function lies in the processing of facial features and the recognition of faces. The amplitude and latency of the N170 serve as markers of cognitive performance, with larger and more rapid N170 responses signaling improved face processing and recognition.

Conversely, the N400, another negative ERP sub-component, materializes around 400 ms after the presentation of a semantic stimulus, such as a word or sentence [34]. The N400 is intimately connected with semantic processing, encapsulating language comprehension, and memory retrieval. Here again, the amplitude and latency of the N400 offer insights into cognitive performance, with larger and more rapid N400 responses indicative of superior semantic processing and comprehension. Each ERP waveform boasts unique characteristics and is influenced by specific factors, as outlined in Table 1.

Table 1
Main Characteristics of P300, N170, and N400 Waveforms [19, 23, 30]

ERP waveforms	Latency(ms)	Amplitude range (μV)	Characteristics and factors
P300	250–350	5–25	Reflects attention, cognitive processing, and task relevance. Amplitude can vary based on stimulus characteristics, attentional demands, and individual differences.
N170	120–200	2–10	Typically observed in response to visual stimuli, particularly faces. Amplitude can be influenced by facial familiarity, emotional expression, and attentional focus. .
N400	300–500	2–8	Occurs in response to semantically meaningful stimuli. Amplitude is affected by semantic processing, stimulus congruity, and contextual integration.

Table 1 offers amplitude ranges as general reference points, drawing from typical observations in prior [19, 23, 30]. However, it is essential to acknowledge that actual amplitude values may exhibit variation contingent upon the specific experimental protocols, recording configurations, and individual dissimilarities. These amplitude ranges, therefore, serve as an initial framework for comprehending these ERPs and the multifaceted determinants affecting the magnitudes. The P300, N170, and N400 ERP sub-components stand as invaluable instruments in elucidating the cognitive processes and performance of individuals within cognitive neuroscience and clinical investigations. Figure 1 shows a simulated ERP waveform with the N170, P300 and N400 sub-components.

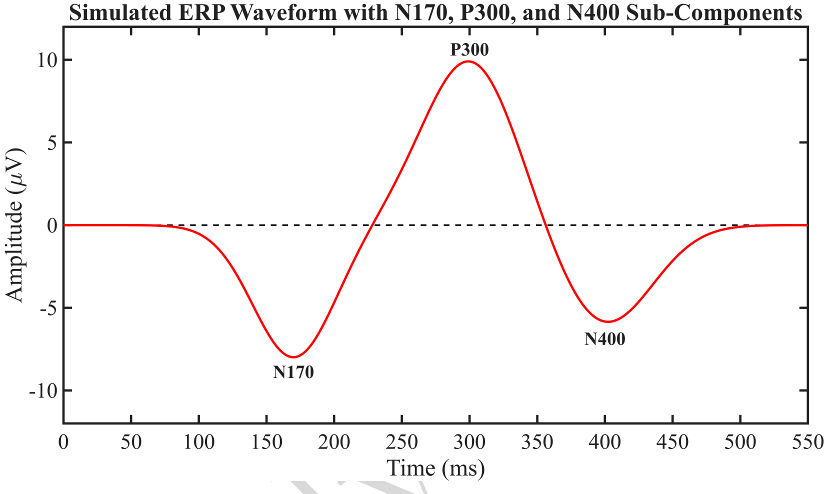

Figure 1. Simulated ERP Waveform with N170, P300 and N400 Sub-Components

3.2. Correlation coefficient

Spearman's rank correlation coefficient is a statistical measure assessing the strength of the relationship between two variables [15]. In the context of human cognitive performance and ERP, it determines the association between the amplitude or latency of ERP sub-components (e.g., P300, N170, N400) and measures of cognitive performance, such as reaction time or accuracy. Spearman's rank correlation coefficient relies on rank order rather than specific numerical values. The coefficient ranges from -1 (perfect negative correlation) to $+1$ (perfect positive correlation), with 0 indicating no correlation. It also reveals the proportion of variability in one variable explained by another. In a study measuring P300 component amplitude in an attention-demanding task and participants' reaction times to target stimuli, Spearman's rank correlation coefficient assesses the association between P300 amplitude and reaction time. A positive coefficient suggests that as P300 amplitude increases, reaction time decreases, signifying better cognitive performance. Therefore, Spearman's rank correlation coefficient is a valuable statistical tool for examining the relationship between ERP sub-components and cognitive performance in studies exploring the neural basis of cognitive processes.

3.3. Distance-based measurement

Euclidean Distance (ED) is a widely employed method in numerous academic disciplines, renowned for its versatility in quantifying the similarity or dissimilarity between data points [27]. Within the domain of cognitive neuroscience, particularly in the analysis of Event-Related Potentials (ERPs) and cognitive performance, ED emerges as a crucial metric [7]. This distance metric, computed by measuring the straight-line separation between two points in a multidimensional space, allows for a nuanced comparison of ERP waveforms, where each data point signifies the waveform's amplitude at a specific time point [7]. The application of ED in the analysis of cognitive performance and ERP sub-components is supported by various empirical studies. For instance, [22] demonstrate the effectiveness of different distance metrics, including Euclidean, in comparing ERP waveforms, while [30] provides insights into the relationship between ERP components and cognitive processes. Smaller ED between ERP waveforms obtained from individuals engaged in cognitive tasks often indicates greater similarity in cognitive performance [7]. Conversely, larger distances suggest greater dissimilarity, implying differences in cognitive processing. Moreover, changes in ED pre and post-cognitive interventions offer valuable insights into the impact of these interventions on cognitive performance. For instance, studies by [12] explore the effects of cognitive interventions on ERP components, shedding light on their potential to modulate cognitive processes. Through the meticulous analysis of ERP waveforms using ED, researchers can unravel the intricate neural mechanisms underlying cognitive processes and their susceptibility to various modulations, including cognitive interventions and individual differences [7]. Thus, ED stands as an indispensable tool in exploring the complex relationship between cognitive performance and ERP sub-components, supported by empirical evidence from cognitive neuroscience research.

4. Methodology

The research framework, as illustrated in Figure 2, comprises three primary stages: 1) data collection, 2) data preprocessing, and 3) data analysis. During the data preprocessing phase, digital filtering, ensemble averaging techniques, and baseline correction are implemented to extract the ERP sub-components from the raw data. Subsequently, in the data analysis stage, the Correlation and Distance-Based approach is employed on the preprocessed ERP waveforms, and the resultant findings are subjected to rigorous statistical testing for significance.

4.1. Data collection

In conventional psychological studies, data collection typically necessitates the involvement of expert psychologists to ensure adherence to ethical standards. However, this study adopted an open-source event-related potential (ERP) dataset obtained through contrast discrimination tasks [1].

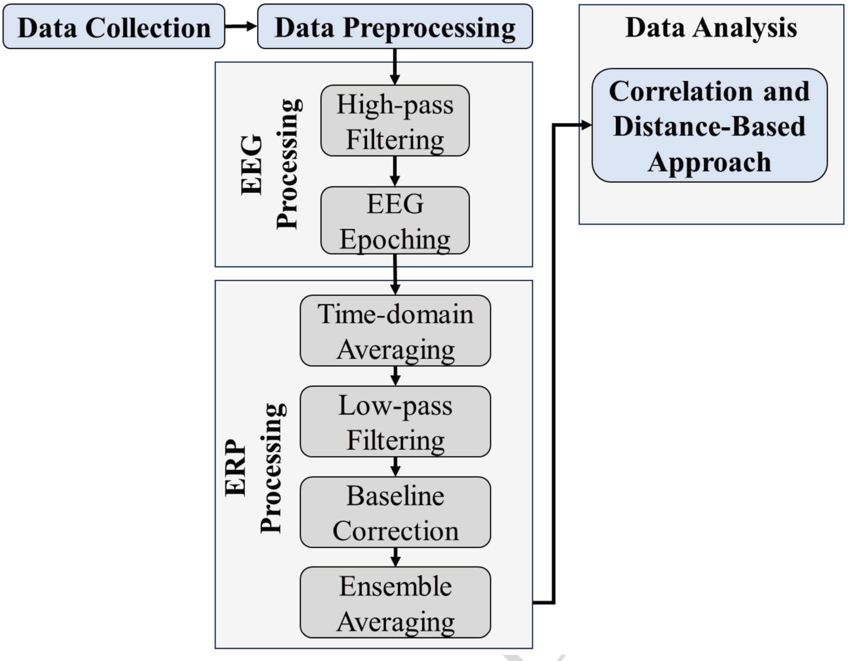

Figure 2. Framework for ERP Analysis Using Correlation and Distance-Based Approach

This innovative approach allowed the investigation to proceed without the direct involvement of specialized psychological experts. The raw brain signal data was acquired using a WaveGuard cap and an ANT Neuroscan EEG system, which incorporated 64 electrodes. While the 10/20 system generally refers to a method for electrode placement, it does not inherently consist of 64 electrodes. Instead, the electrodes were arranged in a manner consistent with the 10/20 system principles, ensuring comprehensive coverage of the scalp. The AFz electrode served as the ground reference. Data acquisition was performed at a sampling rate of 1 kHz utilizing the ASALab software. To pinpoint the P300, N170, and N400 components, electrode placements following the 10/20 system were adopted, covering prefrontal (Fp), frontal (F), temporal (T), parietal (P), occipital (O), and central (C) regions. Additionally, midline sagittal plane electrodes denoted as 'Z' (zero), including FpZ, Fz, Cz, and Oz, were designated as grounding or referencing points. These electrode selections were meticulously made to encompass an extensive array of brain regions relevant to the P300, N170, and N400 components. Channels Pz, P3, P4, and Cz were specifically chosen to effectively capture neural activity linked to the P300 component, known to manifest in these regions [8]. The N170 component, primarily associated with face processing, was targeted using channels Oz, O1, O2, P7, and P8, selected for their significance in the occipital and posterior temporal regions [2]. For the detection of the N400 component, channels Cz and CPz were included, as these central and centroparietal regions are commonly associated with substantial N400 activity [23]. During the experimental procedure, participants were seated in a dimly lit room 57 cm from the display screen. Responses were collected through a mouse interface to indicate observations. The task was divided into five blocks, each comprising an 8-minute trial period with 200 trials per target contrast. Trigger events with infrequent occurrences during human brain signal detection were excluded from the analysis in this study. To summarize, meticulous selection of electrode placements and the experimental design were devised to concurrently capture the P300, N170, and N400 components. These specific channels were chosen considering the distinct requirements for identifying and investigating these components, all within the broader framework of the electrode placement system employed in this study. It is important to note that the experiment excluded the last 25% of the trials (50 trials) due to unusually high noise levels caused by external factors.

4.2. Data preprocessng

4.2.1. EEG processing

In the raw brain signal recordings, a significant presence of noise is a common occurrence, primarily stemming from participant movements and voltage dispersion between different electrodes during data collection. This noise can be effectively eliminated from the raw Brain Signals to enhance the extraction of ERP sub-components. One approach employed for noise reduction is the use of finite impulse response (FIR) filters, which are digital filters capable of removing noise that contaminates the raw Brain Signals across a wide frequency range. FIR filters exhibit linearity in the phase, ensuring enhanced stability during the filtering process, a feature that distinguishes them from infinite impulse response (IIR) filters. Typically, a high-pass filter with a cutoff frequency of 0.1 Hz and a low-pass filter with a cutoff frequency of 30 Hz is applied to brain signal recordings to attain an optimal noise-to-signal ratio. These filters effectively eliminate signals with frequencies falling below or exceeding the specified cutoff frequencies, optimizing the overall signal quality. The convolution equation representing the operation of a finite impulse response filter is presented in Equation (1). This mathematical representation illustrates the process by which FIR filters contribute to the refinement of brain signal data, enhancing the extraction of ERP sub-components.

$$y(n) = \sum_{k=0}^{N-1} \mathrm{b}_k \cdot x(n-k) \tag{1}$$

The elements of the equation can be defined as follows: $y(n)$ represents the output signal, $x(n)$ corresponds to the input signal, N signifies the filter order, and b_{k} denotes the value of the impulse response at the instance denoted as k. These components collectively illustrate the fundamental parameters and variables within the equation, outlining the key factors contributing to the signal processing process.

4.2.2. High-pass filter

High-pass filters are frequently employed in EEG and ERP studies to enhance the statistical power of data. They serve the purpose of mitigating variations in voltage, including skin potentials and gradual voltage offsets [25]. This type of electric filter functions by allowing signals possessing frequencies above the cut-off frequency to pass through while simultaneously attenuating signals with frequencies below this threshold. Notably, high-pass filters exhibit reduced susceptibility to the edge artifacts issue, which can lead to inaccuracies in the calculation of filtered values, especially after the EEG recording. As a result, high-pass filters are commonly administered to the EEG recording before the EEG Epoching step, during which specific time windows are extracted from the continuous single-trial EEG data. This strategic application of high-pass filters serves to optimize data quality and reliability in EEG and ERP investigations. A high-pass filter with a cutoff frequency of 0.1 Hz and an attenuation of 12 dB/octave is applied to the raw Brain Signal in this study.

4.2.3. Ensemble averaging

Ensemble averaging stands as a widely adopted technique in ERP analysis, primarily serving the purpose of noise reduction and the amplification of ERP sub-component signals. At its core, this approach involves the precise alignment and subsequent averaging of multiple ERP waveforms that are time-locked to a specific event of interest. To effectively isolate and extract components such as the P300, N170, and N400 from event-related potential (ERP) waveforms through ensemble averaging, a technique known as time-domain averaging is typically employed. This method entails the meticulous alignment of multiple trials associated with the same type of stimulus, followed by the collective averaging. This process is instrumental in elevating the signal-to-noise ratio and facilitating the extraction of the intended ERP component. The general equation for ensemble averaging can be succinctly expressed as follows:

$$\mathrm{ERP}_{\mathrm{avg}}(t) = \frac{1}{n}\sum_{i=1}^{n}\mathrm{ERP}_i(t) \tag{2}$$

Where $\mathrm{ERP}_{\mathrm{avg}}(t)$ is the averaged ERP waveform at time point t. n is the total number of trials. $\mathrm{ERP}_i(t)$ represents the ERP waveform of the i-th trial at time point t. By repeating this process for all time points, a filtered ERP waveform that highlights the component of interest while reducing random variability can be obtained.

4.2.4. Low-pass filter

In contrast to high-pass filters, low-pass filters operate inversely, attenuating brain signals characterized by frequencies lower than the specified cut-off frequency while allowing signals exhibiting frequencies higher than the cut-off frequency to pass through. In the context of ERP studies, low-pass filters find application in the suppression of noise artifacts, including the noise line and EMG interference within the data [25]. It is pertinent to employ a low-pass filter when working with averaged EEG or ERP waveforms, particularly due to the reduced impact of edge artifacts on shorter waveforms. A low-pass filter with a cut-off frequency of 30Hz and 24db attenuation is applied to the ERP waveform. For optimal filtering performance and the enhancement of spectral resolution, a finite impulse response (FIR) low-pass filter, implemented with a Hamming window as the window design method, is often utilized [10]. The Hamming window, an extension of the Hann window, presents distinctive characteristics, including a heightened side lobe and a more gradual fall-off rate, as compared to the Hann window, as illustrated in Equation (3).

$$w(n) = 0.54 - 0.46\cos\left(2\pi\frac{n}{N}\right) \tag{3}$$

Where $w(n)$ represents the window coefficient, N corresponds to the total number of signals encompassed within the window frame, and n denotes the input signal. These elements collectively indicate the fundamental parameters and variables within the equation, outlining in the signal processing process.

4.2.5. Baseline correction

ERP signals exhibit a time-resolved nature, which implies the presence of temporal drifts or vertical offsets in the electrical signals. These variations in voltage levels over time often result from a range of factors, both internal and external, such as fluctuations in skin hydration and static changes in electrode conditions during the data collection process. To mitigate the influence of these offsets and drifts on the integrity of ERP signals, a fundamental preprocessing technique known as baseline correction is employed in ERP analysis. The core principle behind baseline correction involves the removal of these temporal drifts and offsets from the recorded brain signals. This is achieved by computing the average voltage level during the pre-stimulus interval and subsequently subtracting this value from every data point within the ERP waveform. The application of baseline correction serves the purpose of minimizing variance in the data while effectively segregating the stimulus-induced brain activity from any preexisting neural activity that may have been present before the onset of the stimulus.

4.3. Correlation and distance-based approach

The Spearman's Rank Correlation Coefficient, in conjunction with Euclidean Distance, has been employed to formulate a framework for defining cognitive performance with a focus on the P300, N170, and N400 ERP sub-components. Spearman's Rank Correlation Coefficient serves to quantify the strength and direction of the monotonic relationships that exist between various variables, while Euclidean Distance is utilized to measure the degree of dissimilarity or similarity between vectors representing these ERP sub-components. This proposed approach offers a comprehensive evaluation of cognitive performance based on the P300, N170, and N400 sub-components, encompassing both the interrelationships and the spatial separation. By incorporating both the correlations between these sub-components and the spatial distances, this integrated approach yields a more holistic assessment of cognitive performance. The correlation between the amplitudes of the target waveforms can be computed using Equation (4).

$$\rho = 1 - \frac{6 \cdot \sum d^2}{n \cdot (n^2 - 1)} \tag{4}$$

Where ρ is the correlation coefficient. d is the difference in ranks of corresponding observations. n is the number of observations (e.g., trials or participants). To provide a more specific representation of the variables in the equation for the sum of squared differences between the ranks of amplitudes, in this case, the variables can be denoted as follows:

- $\mathrm{P300}_{\mathrm{ranks}}$: The ranks of P300 across the EEG channels
- $\mathrm{N170}_{\mathrm{ranks}}$: The ranks of N170 across the EEG channels
- $\mathrm{N400}_{\mathrm{ranks}}$: The ranks of N400 across the EEG channels

To calculate the sum of squared differences between the ranks of these variables, the equation is modified as Equation (5).

$$\begin{aligned}\sum d^2 = \sum (P300_{\mathrm{ranks}} - N170_{\mathrm{ranks}})^2 + \sum (P300_{\mathrm{ranks}} - N400_{\mathrm{ranks}})^2 \\ + \sum (N170_{\mathrm{ranks}} - N400_{\mathrm{ranks}})^2\end{aligned} \tag{5}$$

The actual computation of the sum of squared differences would involve substituting the specific ranks of the variables into the equation and performing the summation. As the specific measure of learning performance is used, the experimental design will impact the interpretation of the correlation results. The strength of the correlation in the correlation coefficient (ρ) ranges from -1 to 1. A correlation coefficient of 1 indicates a perfect positive correlation, while a coefficient of -1 indicates a perfect negative correlation and a coefficient of 0 indicates no correlation. The significance of the correlation can be determined using a hypothesis test with a p-value threshold (e.g., p ¡ 0.05). Euclidean distance is applied to measure the correlation between ERP waveforms and human learning performance. The basic idea is to calculate the Euclidean distance between two targeted ERP sub-components and use it as a measure of the similarity. A smaller Euclidean distance indicates a stronger correlation between the two waveforms as in Equation (6).

$$d(x, y) = \sqrt{\sum (x_i - y_i)^2} \tag{6}$$

Where $d(x, y)$ is the Euclidean Distance between two waveforms x and y. x_{i} and y_{i} are the amplitude values of the i-th sample in waveforms x and y, respectively. The Euclidean Distance can be computed as the square root of the sum of squared differences between the amplitudes of corresponding components across EEG channels as follows:

- $P300_i$: P300 amplitudes across EEG channels
- $N170_i$: N170 amplitudes across EEG channels
- $N400_i$: N400 amplitudes across EEG channels

The specific computation of Euclidean Distance for the amplitude of the ERP sub-components is presented as Equation (7).

$$d_{ERP} = \sqrt{\sum(P300_i - N170_i)^2 + \sum(P300_i - N400_i)^2 + \sum(N170_i - N400_i)^2} \tag{7}$$

Where d_{ERP} denotes the squared differences between the targeted ERP sub-components. The $P300_{\text{i}}$, $N170_{\text{i}}$, and $N400_{\text{i}}$ are the amplitudes at index i in the respective vectors. Assigning weights to each component of ERP waveforms (P300, N170, N400) based on the importance or relevance is subjective and can vary depending on the specific research question or context. However, this study provides a general approach for assigning weights W_1, W_2, and W_3 to each component (P300, N170, N400) based on the importance or relevance (normalized to a scale of 0 to 1):

- $W_1 = 0.4$
- $W_2 = 0.3$
- $W_3 = 0.3$

These weighted ERP waveforms reflect the assigned weights based on the important criteria by multiplying the Spearman's Rank Correlation Coefficient by the Euclidean Distance, weighted by the respective weights for each component. The weighted correlation value is calculated for each component using the following Equations:

$$P300_{wcc} = \rho \cdot d_{ERP} \cdot W_1 \tag{8}$$

$$N170_{wcc} = \rho \cdot d_{ERP} \cdot W_2 \tag{9}$$

$$N400_{wcc} = \rho \cdot d_{ERP} \cdot W_3 \tag{10}$$

Where WCC denotes the Weighted Correlation Component for each component. The weighted correlation values are summed up across the ERP sub-components to obtain an overall measure of cognitive performance. The proposed methods combined approach considers the correlation between ERP sub-components (P300, N170, N400) using Spearman's Rank Correlation Coefficient and incorporates the spatial distance using Euclidean Distance. A positive correlation suggests that there is a consistent relationship between the ranks of the P300, N170, and N400 components across the brain channels. Higher ranks in one component are associated with higher ranks in the other components, indicating a similar pattern of response across the channels. The magnitude of the positive correlation coefficient would indicate the strength of the relationship. If the correlation coefficient is close to 1, it suggests a strong positive correlation, meaning that the ranks of the components are closely related and tend to increase or decrease together. If the correlation co-efficient is closer to 0, it indicates a weaker positive correlation. In contrast, the negative correlation coefficient suggests that there is a negative relationship between the ranks of the P300, N170, and N400 components across the Brain channels. This means that ranks in one component tend to be associated with lower ranks in the other components. By applying appropriate weights, this method can capture the relative importance of each component in determining cognitive performance.

5. Experimental results

The ERP sub-components need to be extracted from raw Brain Signals and preprocessed equally before being applied to the Correlation and Distance-Based approach. Initially, a FIR high-pass filter with a cutoff frequency of 0.1 Hz and an attenuation of 12 dB/octave is applied to the continuous single trial Brain signal data. This high-pass filter effectively eliminates noise, optimizing the quality of the Brain Signal data. The effects of the filter on an EEG channel are shown in Figure 3, highlighting the successful noise reduction.

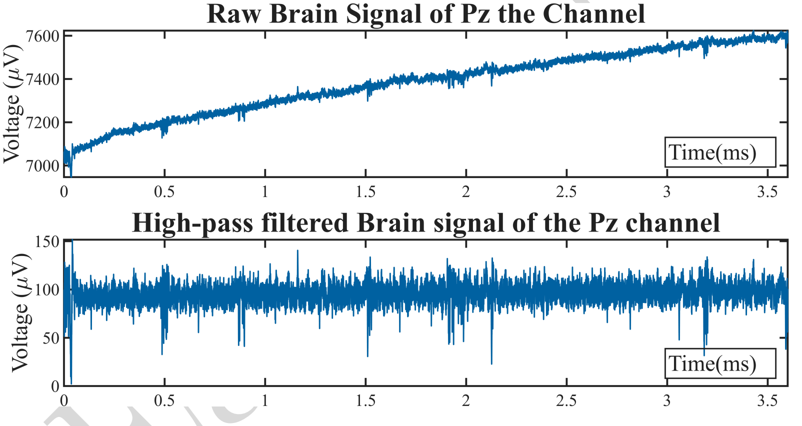

Figure 3. High-Pass Filtered Brain Signal Data of Pz Channel

The high-pass filtered raw Brain Signal is divided into 150 separate trials, each with a 2,400 milliseconds split into 1000 pre-stimulus and 1400 post stimulus duration. These trials are then averaged into a single trial using time-domain averaging to extract the Event-Related Potential signals. This process enhances the signal-to-noise ratio and ensures that the extracted ERP sub-components are representative of cognitive activity.

Table 2 presents the numerical values corresponding to the data points of the Event-Related Potential (ERP) recorded across the Electroencephalogram (EEG) channels within a representative sample following the time domain averaging. Subsequently, a low-pass filter with a cut-off frequency of 30 Hz and 24 db attenuation is applied to the ERP signal across the Brain channels, reducing the impact of noise and further refining the signal quality.

Table 2
Filtered ERP Data

Time (ms)	Amplitude μV									
	Pz	P3	P4	P7	P8	Oz	O1	O2	Cz	CPz
1	95.7	74.4	68.5	-123.7	50.9	42.9	-100.1	77.4	69.8	92.4
2	95.6	74.4	68.4	-123.5	51.0	42.8	-100.2	77.2	69.8	92.4
3	95.6	74.5	68.3	-123.1	51.1	42.6	-100.3	77.0	69.8	92.4
...	...	...	...	...	...	...	...	...	...	...
2399	95.8	74.5	68.5	-123.6	51.3	43.2	-100.1	77.5	69.9	92.3
2400	95.9	74.4	68.6	-123.4	51.4	43.3	-100.0	77.6	69.8	92.3

In addition, a baseline correction will be enacted on the data, wherein a pre-stimulus duration of 1,000 milliseconds will be employed. This correction involves computing the average of the first 1,000 data points in the ERP signal and subtracting this computed value from the entire waveform within each EEG channel. Afterward, 75 evenly distributed data points from the time windows of 250 – 350 ms, 120 – 200 ms, and 300 – 500 ms are extracted to take the amplitudes of the P300, N170, and N400 ERP sub-components respectively, as specified in Table 1. Only 75 data points are selected because it is the greatest number evenly spaced of data points extractable from each ERP sub-component time window. Figure 4 shows the extracted amplitudes of the ERP sub-components from the 10 channels of a sample, indicating the presence of the components of interest.

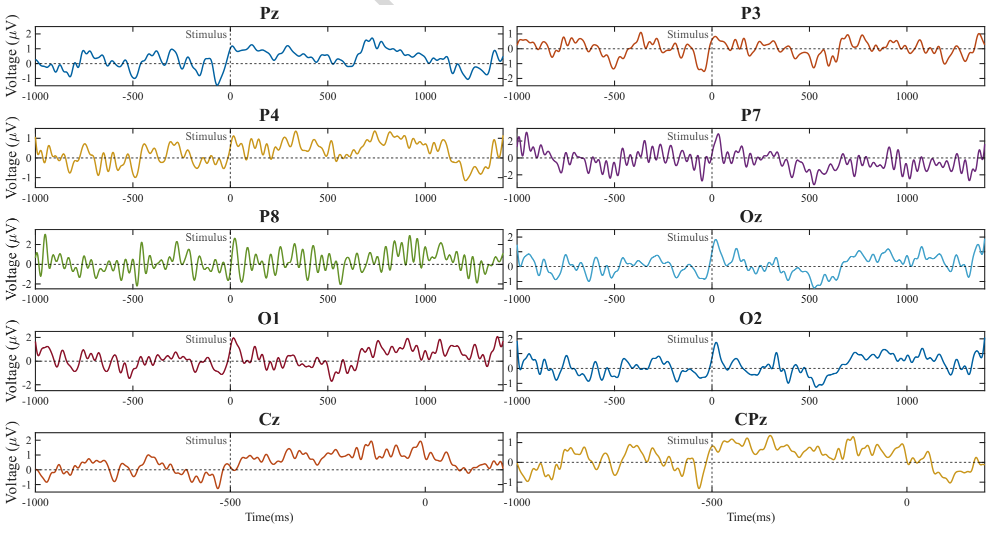

Figure 4. Preprocessed ERP Waveforms Across the Brain Channels

Finally, ensemble averaging is applied to the extracted amplitudes of the ERP sub-components by taking the average of the amplitudes of the 10 channels at each time point. This ensemble averaging provides a consolidated representation of the ERP components and enhances the statistical significance of the analysis. The result is shown in Table 3, indicating the averaged amplitudes of the P300, N170, and N400 ERP sub-components.

Table 3

Ensemble-Averaged Amplitudes of P300, N170 and N400 ERP Sub-Components

P300		N170		N400	
Time (ms)	Activity (μV)	Time (ms)	Activity (μV)	Time (ms)	Activity (μV)
250	0.3930	120	0.7729	300	0.6764
251	0.4056	121	0.7933	303	0.6525
253	0.4242	122	0.8110	305	0.6328
...	...	...	...	...	...
349	0.2277	199	0.2098	497	-0.0548
350	0.1969	120	0.2156	500	-0.0368

To analyze the Event-Related Potential components with the Correlation and Distance-Based approach, the 75 data points of each ERP sub-component are rounded to 2 decimal places, standardizing the data for further analysis. The data points are sorted in ascending order and given a rank based on the values compared to other data points. This ranking process is essential for quantifying the relationships between ERP components. The ranked amplitudes are then used to calculate the sum of squared rank differences between the P300, N170, and N400 ERP sub-components. The resulting sum of squared rank differences, along with the number of ranked data points, is employed to compute Spearman's Rank Correlation Coefficient, utilizing Equation (7).

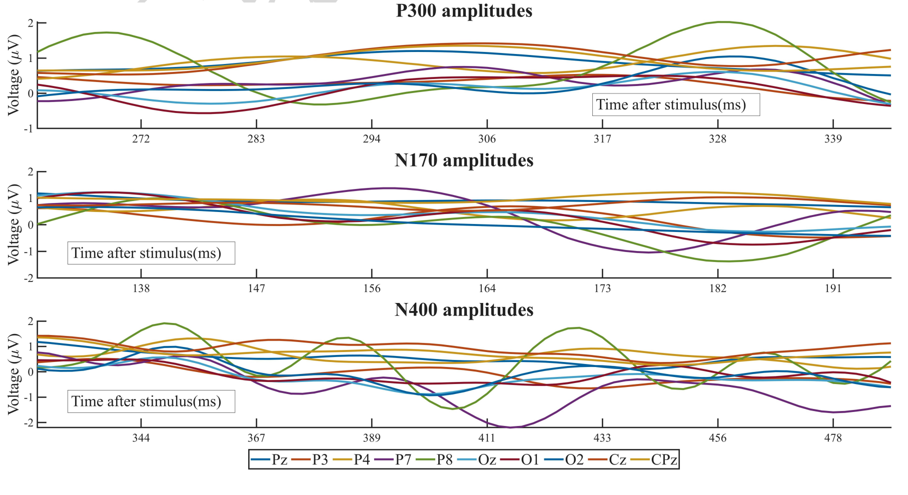

Figure 5. Amplitudes of P300, N170, and N400 ERP Sub-Components

For the distance-based part of the method, the square root of another sum of squared differences between the sorted amplitudes of the ERP sub-components is taken to obtain the Euclidean Distance between the amplitudes of the ERP sub-components. This Euclidean Distance measurement provides insight into the spatial relationships between the ERP components. Finally, the weighted correlation coefficients of each ERP sub-component are calculated by multiplying the Spearman's Rank correlation coefficient with the Euclidean Distance and the assigned weights for the respective ERP sub-component, following Equations (8), (9), and (10) from Section 4.3. This weighted correlation approach allows for a comprehensive assessment of the contributions of each ERP sub-component to cognitive performance. The descriptive statistics of the results obtained from the ERP analysis using the Correlation and Distance-Based approach are shown in Table 4.

Table 4

Results of the Correlation Coefficient and Distance-Based Approach

Variable	Mean	Standard Deviation	Variance	Confidence Interval
Correlation Coefficient (ρ)	0.99	0.01	0.0002	0.01
Euclidean Distance (dERP)	5.50	2.70	7.30	0.93
P300wcc	2.18	1.08	1.16	0.77
N170wcc	1.63	0.80	0.65	0.58
N400wcc	1.63	0.81	0.65	0.58

The examination of correlation coefficients displayed in Table 4 unveils profound insights into the interrelationships among the P300, N170, and N400 ERP sub-components and the impact on cognitive performance. A Spearman's rank correlation coefficient of 0.99, accompanied by a low standard deviation of 0.01, accentuates a positive correlation between the amplitudes of these sub-components and cognitive performance. This implies that greater amplitudes of the P300, N170, and N400 sub-components are indicative of enhanced cognitive performance.

Complementing this insight, the analysis of Euclidean Distance data corroborates the observation. With a mean value of 5.50, a standard deviation of 2.70, and a Confidence Interval of 0.93, the relatively diminutive Euclidean Distance underscores the spatial proximity of data points associated with these ERP sub-components. This suggests that the P300, N170, and N400 sub-components share analogous predictive capacities concerning cognitive performance. The combined evidence from correlation coefficients and Euclidean Distance data underscores a positive relationship among these sub-components, establishing a strong case that higher amplitudes are reflective of superior cognitive performance.

Moreover, the results of paired two-sample t-tests serve to fortify these findings. The p-value of 0.0001 derived from the comparison of $P300_{\mathrm{wcc}}$ with the ERP sub-components underscores the statistical preeminence of $P300_{\mathrm{wcc}}$ in cognitive performance assessment, thus underscoring P300 as the most reliable ERP sub-component for this purpose. Conversely, the p-value of 0.999 arising from the paired two-sample t-test contrasting $N170_{\mathrm{wcc}}$ and $N400_{\mathrm{wcc}}$ implies the absence of a substantial distinction in the efficacy in the evaluation of cognitive performance, reaffirming the equal importance of the N170 and N400 ERP sub-components within this context.

In summation, the systematic scrutiny of correlation coefficients, Euclidean Distance data, and paired t-tests collectively reiterates the positive correlation between the P300, N170, and N400 ERP sub-components and cognitive performance. This evidence strongly suggests that elevated amplitudes within these sub-components correlate with superior cognitive performance. These findings offer invaluable guidance in prioritizing the P300 ERP sub-component in cognitive performance research, while simultaneously acknowledging the equal significance of N170 and N400 in the evaluation of cognitive performance.

6. Discussion and conclusion

6.1. Discussion

The identification of cognitive performance in humans using event-related potentials (ERP) has been a topic of extensive research for several decades. In recent years, significant advancements have been made in the field, particularly in the development of advanced techniques and methods that enable more precise and dependable measurements of cognitive performance through ERP analysis. Our experimental results align with these advancements by demonstrating the effectiveness of filtering and preprocessing techniques in enhancing the quality of Brain signal data, which is crucial for accurate ERP analysis.

A notable recent development involves the application of machine learning algorithms to classify ERP waveforms. Deep learning and support vector machines, among other machine learning algorithms, have shown promising outcomes when utilized to analyze ERP data. These algorithms possess the capability to identify patterns and correlations within ERP data that may not be readily discernible to human observers [32] [3]. This is particularly relevant to our study, where the Correlation and Distance-Based approach was used to analyze the ERP sub-components, providing a robust method for assessing cognitive performance.

Moreover, recent progress in ERP research involves the utilization of high-density EEG systems, which enable the recording of ERP data with superior spatial resolution. This advancement offers the potential to extract more detailed information about the neural processes underlying cognitive performance [33], enhancing the significance of our findings related to the P300, N170, and N400 sub-components. The integration of multimodal imaging techniques, such as combining EEG with functional magnetic resonance imaging (fMRI), has facilitated a more comprehensive understanding of the neural mechanisms associated with cognitive performance [5, 9], further supporting the potential applications of our study.

In addition to investigating cognitive performance, recent studies have focused on utilizing ERP data to develop brain-computer interfaces (BCIs) for individuals with disabilities [38]. The utilization of ERP data in the development of BCIs has demonstrated encouraging results, enabling individuals with disabilities to control devices such as prosthetic limbs and communication devices [13]. These advancements highlight the broader implications of ERP research, extending beyond cognitive performance assessment to practical applications that can significantly impact individuals' lives.

6.2. Conclusion

The correlation analysis conducted in this study has yielded valuable insights into the associations between the P300, N170, and N400 event-related potential (ERP) subcomponents and cognitive performance. These ERP sub-components, which are linked to various cognitive domains, have emerged as potential biomarkers for evaluating cognitive abilities in educational and training settings. The strong positive correlation, as indicated by Spearman's rank correlation coefficient of 0.99 and a low standard deviation of 0.01, underscores the relationship between the amplitudes of these subcomponents and cognitive performance.

The high-pass filtering, and time-domain averaging applied to the raw Brain signal data effectively enhanced the signal-to-noise ratio, allowing for clear extraction of ERP sub-components. The subsequent application of low-pass filtering and baseline correction further refined the signal quality, enabling precise measurement of the P300, N170, and N400 amplitudes. The Euclidean Distance analysis substantiates the strong correlation observed, revealing a relatively small distance between the ERP sub-components, which indicates similar predictive power regarding cognitive performance.

The results of paired two-sample t-tests reinforce these findings. The p-value of 0.0001 in the comparison between $P300_{\mathrm{wcc}}$ and the N-group ERP sub-components highlights the statistical superiority of $P300_{\mathrm{wcc}}$ in assessing cognitive performance. In contrast, the paired two-sample t-test between $N170_{\mathrm{wcc}}$ and $N400_{\mathrm{wcc}}$, with a p-value of 0.999, indicates no significant difference in their effectiveness in assessing cognitive performance. This underscores the equal importance of the N170 and N400 ERP sub-components in this specific context.

In summary, the study's results demonstrate a positive correlation between the P300, N170, and N400 ERP sub-components and cognitive performance, suggesting that higher amplitudes of these sub-components are indicative of superior cognitive performance. The study emphasizes the significance of the P300 sub-component while also recognizing the necessity of N170 and N400 in the assessment of cognitive performance. These findings offer valuable insights for future research endeavors and practical applications in the field of cognitive performance assessment.

6.3. Limitations and future works

There are several limitations to studies that aim to identify cognitive performance using ERP. One of the main limitations is that the quality of the ERP signal is influenced by various factors such as age and gender, mental state, and the type of EEG equipment used for the participant. Additionally, the process of collecting and analyzing ERP data is time-consuming and requires significant expertise, which can limit the practicality and scalability of the approach. Besides, ERP signals may be influenced by other factors besides cognitive performance. For example, external stimuli such as sounds or visual cues can trigger certain ERP sub-components, which may not necessarily reflect cognitive performance. Moreover, different individuals may have varying levels of baseline ERP activity, which can affect the interpretation of ERP signals. Furthermore, there is a lack of consensus on the precise relationship between ERP sub-components and cognitive performance. While some studies have reported strong correlations between specific ERP sub-components and cognitive abilities, others have reported weak or inconsistent relationships. The complex nature of cognitive performance, which involves multiple cognitive processes and neural networks, makes it difficult to identify specific ERP sub-components that can accurately predict cognitive performance. Finally, there are ethical and privacy concerns related to the use of ERP signals for cognitive assessment. The collection and analysis of brain activity data may raise concerns about the confidentiality and privacy of the individual, as well as potential discrimination based on cognitive ability. Despite these limitations, the use of ERP signals for cognitive assessment shows promises and has the potential to provide valuable insights into cognitive performance. Ongoing research is focused on addressing these limitations and developing more accurate and reliable methods for identifying cognitive performance using ERP signals.

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Declarations

Ethical Approval

This study did not involve any human or animal subjects, as it utilized an open-source event-related potential (ERP) dataset obtained through contrast discrimination tasks at the York Biomedical Research Institute (YBRI), University of York, England. Therefore, ethical approval, consent to participate, and consent to publish were not applicable.

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Availability of data and materials

The dataset utilized in this study is an open-source event-related potential (ERP) dataset obtained through contrast discrimination tasks at the York Biomedical Research Institute (YBRI), University of York, England. The dataset can be accessed through the official channels of the YBRI. For inquiries regarding data access, please contact Associate Professor Daniel Baker, a distinguished senior lecturer at the YBRI, who provided the necessary permissions for the implementation of the dataset.

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