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Assessing the impact of stimulation environment and error probability on ErrP EEG response, detection and subject attention: an explorative study

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Objective: This study aims to investigate the impact of stimulus environments (Virtual Theatre vs Monitor) and error probabilities (20% vs 50%) on attentional states, Error Potentials (ErrP), and machine learning classification performance.

Approach: EEG signals were recorded using different protocols, and features were extracted for subsequent analysis from single-trial response and attention level was computed from the second preceding error processing stimulation.

Results: The results indicate significant differences across conditions: the Monitor environment consistently elicited higher and faster ErrP responses and elevated attentional states compared to Virtual Theatre. Additionally, classification performance in the Monitor environment outperformed Virtual Theatre consistently. Further analysis revealed that the 20% error probability protocol yielded increased ErrP responses, heightened attentional states, and superior classification performance compared to the 50% protocol. Classification performance under the 20% error probability condition consistently exceeded 75% validation and test sets. Moreover, a significant correlation between attention-related features and ErrP characteristics was observed, highlighting the intricate relationship between error processing and attentional engagement.

Relevance: These findings underscore the importance of considering stimulus environments and error probabilities in cognitive neuroscience research and machine learning applications. Understanding these factors can inform experimental design and model development, ultimately advancing our comprehension of cognitive processes and enhancing real-world applications of machine learning algorithms.

KEYWORDS

brain computer interfaces, electroencephalography, error related potential, signal processing, virtual reality, machine learning

1 Introduction

In recent years, significant progress has been made in the development of Brain-Computer Interfaces (BCIs) that enable the control of external devices by interpreting brain activity (Wolpaw et al., 2000). The electroencephalographic (EEG) signal plays a crucial role in this process, but it is inherent complexity and stochastic nature make reliable and accurate classification of brain activity challenging. Consequently, BCI systems may misinterpret user intentions, leading to errors (Lotte et al., 2018). Such misclassifications can have a detrimental impact on system performance and easily frustrate users (Spuler et al., 2012).

To address these challenges and improve the accuracy of BCI systems, researchers have investigated the use of Error Potentials (ErrP) (Buttfield et al., 2006; Chavarriaga et al., 2010). ErrP is an evoked potential that occurs when a subject perceives an error, whether self-generated, generated by another subject, or by an external device such as a BCI system (Falkenstein et al., 2000; Fu et al., 2023). Detecting ErrP during a BCI experiment enhances classification accuracy, enabling the system to repeat tasks that resulted in erroneous outcomes. For instance, Dal Seno et al. (2010) utilized detected ErrP signals to correct the output of a P300 speller, and their study demonstrated improved classification performance of the overall BCI system.

The ErrP is an innate response to erroneous events whose characteristic waveform features a negative peak at around 250 m after the error, followed by a positive peak at 320 m and a subsequent negative peak at 450 m. In terms of frequency content, the EEG signal recorded after an error event is particularly prominent in the delta (1–3 Hz) and theta (5–8 Hz) brain rhythms Ferrez et al. (2008). However, the extent to which cognitive abilities affect the temporal and frequency characteristics of ErrP signals remains unclear (Farabbi and Mainardi, 2022). Specifically, limited research has investigated whether a subject's level of attention during ErrP-based BCI experiments can influence the evoked ErrP response to errors.

Moreover, the influence of environmental factors on ErrP elicitation remains poorly understood, despite the growing integration of Augmented or Virtual Reality environments in modern BCI systems. Vourvopoulos et al. (2019) utilized a virtual reality (VR) setup to simulate rowing a boat and facilitate upper limb Motor Imagery in stroke patients. Similarly, Škola and Liarokapis (2018) employed VR to enhance Motor Imagery in a video game contest, leading to a more engaging protocol and a heightened sense of embodiment for the participants. Those studies investigate Motor Imagery but, considering the rising interest in VR/AR environments for BCI systems, it becomes also crucial to investigate the impact of such environments on innate brain responses, such as ErrP, which currently remains unclear.

Several studies have investigated the impact of virtual reality environments on cognitive processing and task performance. Of particular relevance to our research, Szpak et al. (2019) demonstrated that VR exposure can induce significant alterations in visual processing and cognitive performance that persist beyond the immediate VR experience. These effects were found to be independent of traditional cybersickness symptoms, suggesting a distinct cognitive adaptation mechanism to virtual environments, especially in subjects with few experience in using VR systems. Additionally, Mittelstadt et al. (2019) explored how VR-based training environments affect cognitive load and task performance, finding that the virtual environment itself can impose additional cognitive demands on users, potentially affecting their ability to process and respond to stimuli effectively.

One study by Falkenstein et al. (1995) investigated the effects of error feedback probability on event-related brain potentials (ErrP) and attentional mechanisms. The researchers found that when participants were less likely to receive erroneous feedback, there was a significant increase in the amplitude of the ErrP component, suggesting heightened neural responses to errors. This enhanced ErrP response was indicative of greater attentional resources being allocated towards error processing. Similar findings were found in the studies by Feng et al. (2020).

Furthermore, another study by Hajcak et al. (2003) explored the impact of varying error feedback probabilities on attentional mechanisms. They observed that lower error rates led to improved performance on subsequent tasks requiring error monitoring, indicating a beneficial effect of increased error feedback probability on cognitive control strategies.

In addition, research by Gehring and Fencsik (2001) studied the neural mechanisms underlying error processing in the context of different error feedback probabilities. They proposed that variations in error feedback likelihood could modulate the activity of the anterior cingulate cortex, a brain region implicated in error monitoring and cognitive control. Specifically, higher error rates were associated with greater activation in the anterior cingulate cortex, suggesting a link between error feedback probability, neural responses to errors, and attentional mechanisms.

In other Evoked Potentials stimulations, as visual P300 elicitation, it is usually implemented an oddball paradigm, where an odd (less likely stimulus) is alternated with a standard stimulus (more likely stimulus). Various studies affirm that odd stimuli are able to elicit a more pronounced response as reported in Verleger and Śmigasiewicz (2020) and De Venuto and Mezzina (2021).

In view of the aforementioned considerations, this study investigates if variations in attention and engagement levels (provided by different environments) can modulate the brain's response to error and potentially affect its perception. To accomplish this, we devised an innovative protocol called "Racing Mistakes" to elicit ErrP within a gaming environment. The protocol was implemented in two distinct settings: a conventional monitor-based setup and an immersive VR room. Subsequently, only in the Monitor setting, the protocol was tested again lowering the probability of giving an erroneous feedback to 20% in order to assess the influence this change can have on ErrP realization and subject's attention level during the experimental protocols. To evaluate brain response we performed an analysis of the EEG signals obtained from participants in both environments and protocols, with the aim of identifying differences.

Based on the previous considerations, we hypothesize that both the experimental environment and error probability will significantly influence subjects' brain responses to errors. Specifically, we expect that the VR environment will produce a dual effect: while increased immersiveness should enhance attention and potentially strengthen error detection mechanisms, subjects' limited familiarity with VR technology might introduce additional cognitive load, potentially interfering with error processing and distracting the user from the task. Additionally, we hypothesize that reducing error probability to 20% will enhance the amplitude of the ErrP response, similar to the increased neural responses observed in other evoked potentials under oddball paradigms. Both factors are expected to modulate subjects' attention levels throughout the experimental protocols.

This research aims to shed light on the potential impact of environmental factors, probability of erroneous feedback and

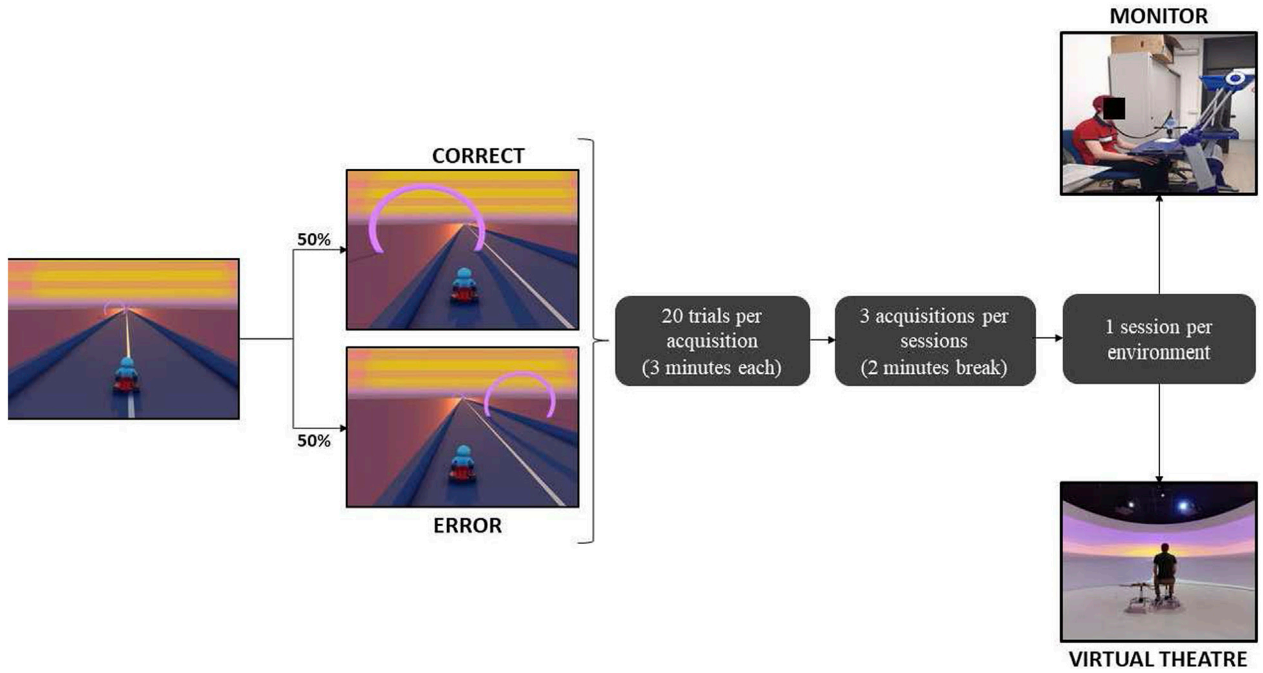

FIGURE 1
Experimental protocol.

attention on the processing of errors and the subjective perception thereof.

2 Materials and methods

2.1 ErrP stimulation protocols

To investigate the differences in ErrP response and attentional states introduced by different environments and the probability of erroneous events a specific experimental protocol was designed. A cohort of 17 university students (7 male, mean age: 21.8 ± 0.77 years) participated in the Error Potential elicitation study. Individuals with visual impairments were excluded to prevent artifacts potentially arising from visual fatigue. The elicitation was conducted using a custom-developed Unity game engine software, and data from all screened participants were included in the subsequent analysis. Participants were instructed to watch a video (titled "Racing Mistakes") featuring a car navigating a road with randomly appearing checkpoints represented as bridges (rings) on either the left or right side of the street. The car had a 50% probability of approaching the checkpoint or moving on the opposite side of the street. When the car missed a checkpoint, it was expected to elicit an ErrP (Error Potential).

Each participant experienced a total of 20 checkpoints during the data acquisition process. The stimuli were presented in two distinct environments across two different sessions in a within participants experimental design in order to assess differences between environments. We randomised which session each participant completed first to prevent order effects from biasing the results. One session occurred in a laboratory setting, where participants viewed the video on a high-quality RGB monitor (resolution of 1,280 × 1,024 and an 8-bit intensity) ensuring optimal visual presentation. The other session occurred in a Virtual Theatre (VT) equipped with Virtual Reality technology. The VT is designed as a 360° cylindrical space with a diameter of 7 m, utilizing an advanced multi-projector system for complete immersive experiences. The projection system consists of six projectors in total:

- Four projectors are strategically positioned to cover the cylindrical walls, with each side projector responsible for rendering more than 90°of the curved surface. These projectors feature intentional overlap zones to ensure seamless calibration and continuous imagery across the entire circumference
- Two additional projectors are dedicated to floor projection, creating a complete immersive environment from ground to walls implementation of the stimuli.

The participants were tested three times consecutively throughout each session with a 2-minute break between each acquisition. The diagram of the complete protocol is depicted in Figure 1. The complete experimental procedure lasted approximately 1 hour per participant. This included 20 min for EEG setup and subject preparation, 10 min for computer setup, and approximately 15 min for the experimental trials. The trial period consisted of three 3-minute trials, with 2-minute breaks between each trial.

Following the acquisition in both settings, the decision was made to expand our protocol within *Monitor* environment to another group with identical numbers, but with a 20% probability of error instead of 50%. This was done to evaluate how the level of surprise affects both the erroneous response and the attentional state of the subjects. It has been chosen a new group of participants for this protocol rather than the original one to avoid potential habituation effects, as the first population had already developed familiarity with the protocol. The selection of 50% and 20% error probabilities was purposeful and grounded in existing literature. The 50% error rate is commonly used in ErrP studies Fu et al. (2023). The 20% error rate was specifically chosen based on oddball paradigm experiments for evoked potential elicitation (particularly P300), where this probability is frequently employed Verleger and Śmigasiewicz (2020), Feng et al. (2020).

All participants signed an informed consent before participating in the study and the protocol was approved by Ethics Committee of Politecnico di Milano (Opinion n.29/2021).

2.2 Data acquisition and pre-processing

During each session, the EEG signals were recorded (512 Hz, sampling rate) using a cuff equipped with 64 electrodes and conductive gel, which were carefully placed on the subject's scalp. The EBNeuro BE Plust LTM amplifier (EBNEURO, Florence, Italy) was used to acquire the signals and to transmit them to a PC via Bluetooth. In order to achieve accurate synchronization of the EEG signals with specific events, such as the timing of erroneous or correct movements of the car, the timing of the trigger was sent to the PC using the Lab Streaming Layer protocol.

The recorded EEG signal underwent several pre-processing steps. First, the signal was band-pass filtered (1–40 Hz) using a 5th-order Butterworth filter to attenuate high-frequency components associated with muscle activity and to preserve frequency information relevant for our analysis. Subsequently, channels exhibiting poor quality were identified and eliminated. These channels may have been affected by electrode issues, resulting in little or no detectable activity. To address artefacts originating from various sources such as blinking or saccadic eye movements, Independent Component Analysis (ICA) was employed. To mitigate the influence of common noise shared across channels, the Common Average Rereferencing technique was utilized. As a final step, the previously removed channels were treated as missing data and introduced into the EEG data through spatial interpolation.

2.3 Single trial estimation

To extract single-trial ErrP responses, we employed a single–sweep analysis based on the Subspace Regularization method (Vauhkonen et al., 1998). The method represents the recorded EEG signal (z in Equation 1) as a linear combination of s, the signal of interest (also referred to as the source), and, v, the noise resulting from the measurement process:

$$z = s + v = H\theta + v \tag{1}$$

where the source signal is estimated as a linear combination of basis vectors (i.e., H). The goal of subspace regularization is to find the optimal basis vectors and parameters (i.e., θ) by minimizing the contribution of estimated noise (i.e., v). In this study, the noise properties were estimated from the background EEG activity recorded during the second preceding the stimulation. It has been shown by Ranta-aho et al. (2003) that an estimate of the source signal ($\hat{s}$) can be obtained using Equation 2:

$$\hat{s} = H\left(H^T * C_v^{-1}H + \alpha^2 H^T\left(I - K_s K_s^T\right)H\right)^{-1} H^T C_v^{-1} z \tag{2}$$

where K_s is the eigenvector of the correlation matrix of z, C_v is the covariance matrix of the noise and α is a regularization parameter.

2.4 Data analysis

The EEG signal was comprehensively analyzed in temporal, frequency, and spatial domains to gain a thorough understanding of the brain's response following erroneous stimulation and to compare these responses between the two environments.

2.4.1 Time and frequency domain features

Time and frequency domain features were extracted from the sources $\hat{s}$ at electrodes Cz and FCz, those are the areas where most of the ErrP-related activity is expected to occur (Falkenstein et al., 2000; Fu et al., 2023). In the time domain, essential ErrP features [as reported by Falkenstein et al. (2000); Fu et al. (2023)] such as peak amplitude and latency were extracted for the positive peak within the 200 – 400ms interval after the stimulus, and for the negative peak within the 300 – 500 ms interval after the stimulus. The latency of the negative peak was calculated relative to the positive peak to account for delay propagation effects.

In the frequency domain, the Power Spectral Density (PSD) of the ErrP (segments long 1s after error stimulus onset) was calculated using the Welch method, and the amplitudes of the highest peaks in the δ frequency range (i.e., $1 - 3$Hz) and θ frequency range (i.e., $4 - 7$Hz) were extracted for each epoch. These bands were chosen since studies from Ferrez et al. (2008) and Fu et al. (2023) suggest those as the most responsive bands to erroneous stimuli.

2.4.2 Time-frequency features

Event-Related Spectral Perturbation (ERSP) (Makeig, 1993) was computed for the ErrP trials in both environments to provide a simultaneous description of the ErrP-related response in both the time and frequency domains. ERSP describes the average changes in power with respect to a baseline level. The Wavelet Transform, specifically the Morlet wavelet, was employed to extract frequency information over time. The ERSP was calculated for all channels using the formula in Equation 3:

$$ERSP = 10 \cdot \log\left(\frac{P_{\text{trial}}}{P_{\text{baseline}}}\right) \tag{3}$$

where P_{trial} represents the power computed on a 1s window following each erroneous stimulus, and P_{baseline} represents the power computed during the 1 s window preceding the stimulus. In particular, the ERSP represents the power variation in the

TABLE 1 Parameters for quantitative assessment of attention status. The frequency bands considered, the measurement area and the correlation with the attention state are shown.

Frequency−Bands	Area	Correlation with attention status	References
Beta Band $(13-30Hz)$	1) Occipital 2) Parietal	Positive	Lutsyuk et al. (2006)
$\frac{BetaBand}{ThetaBand}$ $Beta\,(13-18Hz)$ $Theta\,(4-7Hz)$	1) Frontal 2) Parietal	Positive	Ogrim et al. (2012)
$\frac{BetaBand}{ThetaBand+AlphaBand}$ $Alpha\,(8-13Hz)$ $Beta\,(13-18Hz)$ $Theta\,(4-7Hz)$	Sum in channels: Cz, Pz, P3, P4	Positive	Barry et al. (2003) Ke et al. (2021)
$\frac{BetaBand}{AlphaBand}$ $Beta\,(13-30Hz)$ $Alpha\,(8-13Hz)$	1) Channel P4 2) Channel Pz	Positive	Braboszcz and Delorme (2010) Bacigalupo and Luck (2019)
$\frac{ThetaBand}{AlphaBand}$ $Beta\,(13-30Hz)$ $Alpha\,(8-13Hz)$	Theta band in Frontal zone Alpha Band in Parietal zone	Positive	Bacigalupo and Luck (2019) Gola et al. (2013)

logarithmic scale after the event with respect to the baseline represented by the second before the stimulus.

2.4.3 Spatial features

Spatial features were analyzed to examine the spatial characteristics of the ErrP response. The ERSP averaged across the δ, θ, and α–frequency bands (Falkenstein et al., 2000; Ferrez et al., 2008) for each time bin, obtained from all electrodes, was represented using topoplots (Duffy et al., 1979; Michel and Murray, 2012). Topoplots are graphical 2D representations of a specific variable on the scalp. In our case, we represent the ERSP computed for each electrode in the different frequency bands and for each time bin. In the areas where no electrode is placed, the value is extracted through cubic spline interpolation of the ERSP computed in the nearest electrodes. We decided to analyze α-related activity since studies by Clayton et al. (2018) and Klimesch (2014) have shown that decreased α oscillations can indicate sustained attention. Based on this relationship, we examined the fluctuations in α activity during ErrP stimulation.

2.4.4 Attention features

In this study, we analyzed attentional features gleaned from previously published literature (Lutsyuk et al., 2006; Ke et al., 2021; Braboszcz and Delorme, 2010; Bacigalupo and Luck, 2019; Ogrim et al., 2012; Gola et al., 2013; Barry et al., 2003). The primary objective of the chosen studies was to quantitatively evaluate the attentional states of individuals without cognitive disorders while engaging in various tasks, such as those encountered in work or educational settings. Conversely, certain studies aimed to explore differences in these parameters between individuals without cognitive disorders and those with attention-related cognitive impairments. The selected parameters are delineated in Table 1, wherein each parameter specifies the frequency band under analysis, the measurement zone, and the correlation between the parameter and attention levels. These features were derived from the frequency analysis of Section 2.4.1 and were computed in the second preceding the erroneous stimulus.

2.4.5 Statistical analysis

To evaluate the differences between the two environments, as the data did not adhere to normal distributions, we employed the Mann-Whitney rank-sum test. This statistical test was utilized to assess significant differences between the environments and between surprise levels specifically in relation to the temporal and frequency domains of electrodes FCz and Cz.

Permutation statistics were employed to focus the analysis solely on significant values of the ERSP. This involved zeroing out non-significant features in the output plots, enabling a more targeted investigation. All statistical comparisons were performed using MATLAB R2021a, with a significance level set at 5% $(p < 0.05)$.

2.5 ErrP classification

The examination of ErrP elicitation differences has extended to assessing classification performance in discerning between erroneous and correct events. To achieve this objective, an LDA classifier will be trained for each environment and each level of surprise, utilizing ErrP temporal and frequency domain features outlined in Section 2.4.1.

Model validation is executed through a 5-fold cross-validation approach. Balancing of the training set is accomplished utilizing the ARX method expounded in Farabbi et al. (2022). The ARX model

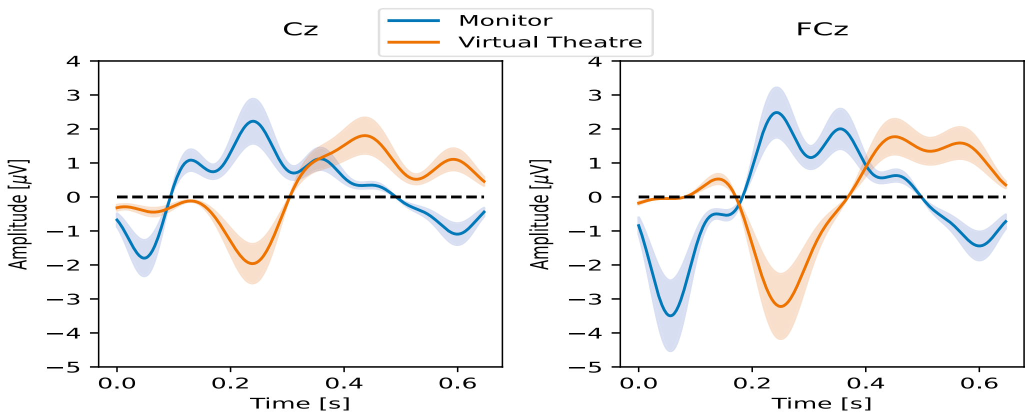

FIGURE 2
Grand Averages of ErrP trials for one subject in the Monitor (left) and VT (right) environments for electrodes Cz (blue) and FCz (orange) with the related confidence interval.

combines background EEG activity with characteristic error-related waveforms and can be expressed as in Equation 4:

$$y_i(t) = \sum_{j=1}^{p} a_j y_i(t-j) + \sum_{k=1}^{q} b_k u(t-k-d) + e_i(t) \tag{4}$$

where $y_i(t)$ represents the EEG signal at epoch i, with a_j and b_k being the model coefficients for the autoregressive and exogenous components, respectively. The exogenous input $u(t)$ models the ErrP waveform, while $e_i(t)$ represents a white noise process. The ErrP waveform $u(t)$ is obtained through synchronous averaging of epochs containing error potentials. For robust estimation, we exclude epochs that exhibit either a root mean squared (RMS) difference exceeding two standard deviations from the mean, or a maximum slope greater than two standard deviations from the average maximum slope across epochs.

Model identification is performed by estimating the coefficients through least squares optimization as described in Equation 5:

$$F_i(t) = \frac{1}{N} \sum_{j=1}^{N} \left(y_i(t) - \hat{y}_i(t)\right)^2 \tag{5}$$

where N denotes the number of time samples, and $\hat{y}_i(t)$ represents the model's prediction. The optimal model orders are selected using the Akaike Information Criterion (AIC), and model validation is performed using Anderson's test with a 95% confidence interval to verify residual whiteness.

For data augmentation, we generate synthetic epochs by applying three distinct modifications to the exogenous input. First, as reported in Equation 6, amplitude scaling modifies the waveform magnitude:

$$u_{new}(t) = a \cdot u(t), \quad a \in [0.5, 1.5] \tag{6}$$

Second, we introduce additive white noise with zero mean and variable standard deviation as in Equation 7:

$$u_{new}(t) = u(t) + WN(\mu = 0, \sigma), \quad \sigma \in [0.1, 0.8] \tag{7}$$

Finally, in Equation 8, temporal warping is applied to modify the signal timing:

$$u_{new}(t) = u(a \cdot t), \quad a \in [0.75, 1.25] \tag{8}$$

These transformations, applied individually or in combination, generate diverse yet physiologically plausible synthetic ErrP epochs while maintaining the essential characteristics of the original signals.

We evaluate model performance comprehensively using balanced accuracy, precision, recall, and F1-score on both validation and test data.

3 Results

This section presents the outcomes of the comparison between two distinct environments for ErrP elicitation, namely, the Monitor and VT, followed by a comparison based on the probability of error occurrence (i.e., 20% and 50%). For each protocol comparison, the results will be initially presented concerning neurophysiological responses, encompassing both ErrP realization and attention features. Subsequently, the section will delve into the evaluation of LDA classifier performance. Figure 2 illustrates the Grand Average of the Error Potential (ErrP) signals computed from the Cz and FCz electrodes in both the Monitor and VT environments for one subject as an example. The shape of ErrP shows the expected waveforms in both environments; however, noticeable differences can be observed between them. Specifically, during the Monitor stimulation, the ErrP exhibits distinct positive and negative peaks at the expected latencies. In contrast, in the VT environment, the amplitudes of both peaks are attenuated. Additionally, the VT environment elicits delayed responses, as clearly depicted in Figure 2 with the timing of the initial maximum peak indicated by a red line.

3.1 Monitor vs. Virtual Theatre

3.1.1 Neurophysiological response

The observed qualitative differences in the Grand Averages are further supported by the distribution of computed time domain features, as presented in Figure 3A. This figure

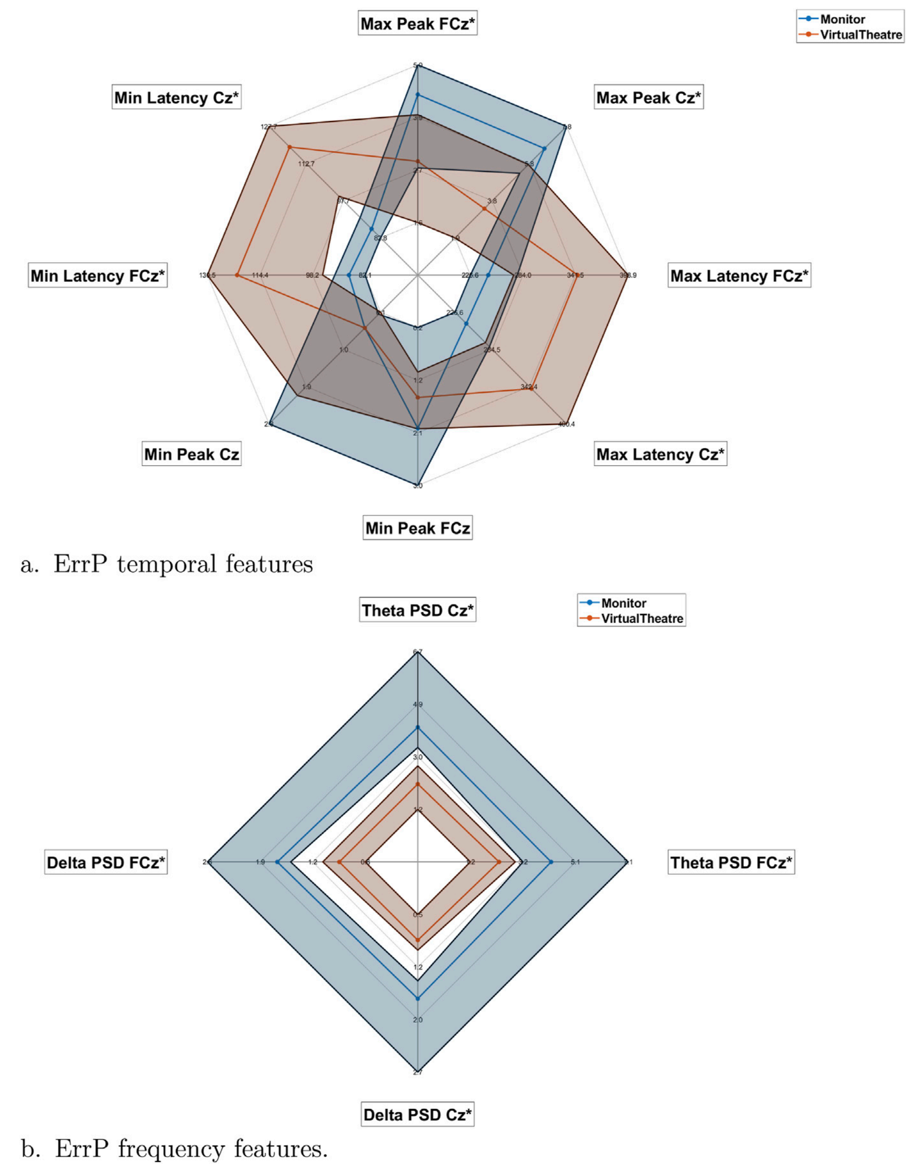

FIGURE 3
Radar plots of the temporal **(A)** and frequency **(B)** features for the Monitor (blue) and VT (orange). For both classes and each feature is reported shaded the interquartile range.

provides information on the medians, 25th and 75th quartiles of each feature's distribution in the Monitor and VT environments, specifically for electrodes FCz and Cz. All the reported features show significant differences in the two environments $(p-value<0.05)$, beside the minimum peak at the two examined electrodes.

The frequency domain features further substantiate the presence of differences between the two environments. The comparison of average PSD values in the δ and θ bands for the Monitor and VT environments is presented in Figure 3B. The results reveal a significant increase in activation (i.e., $p<0.05$) in the Monitor environment for both bands across most acquisitions. Notably, the θ band exhibits the most substantial increase.

The results of ERSP analysis of electrodes Cz and FCz in both environments is depicted in Figures 4A, B. These figures provide insights into the observed activation patterns and differences between the two environments. In the Monitor environment, notable activation is observed in the expected frequency bands and latencies. Furthermore, after 400 ms, this activation extends to the alpha band. Conversely, in the VT environment, the activation is nearly absent in electrode FCz, and there is a delay in activation observed in electrode Cz. Both plots also include a representation of the difference in activation between the Monitor and VT environments. The image supports the findings reported before, with a higher activity in the Monitor environment. Figure 5 illustrates the spatial ERSP at 100, 300 and 500 ms in the two different stimulation environments, as well as for the δ, θ, and α

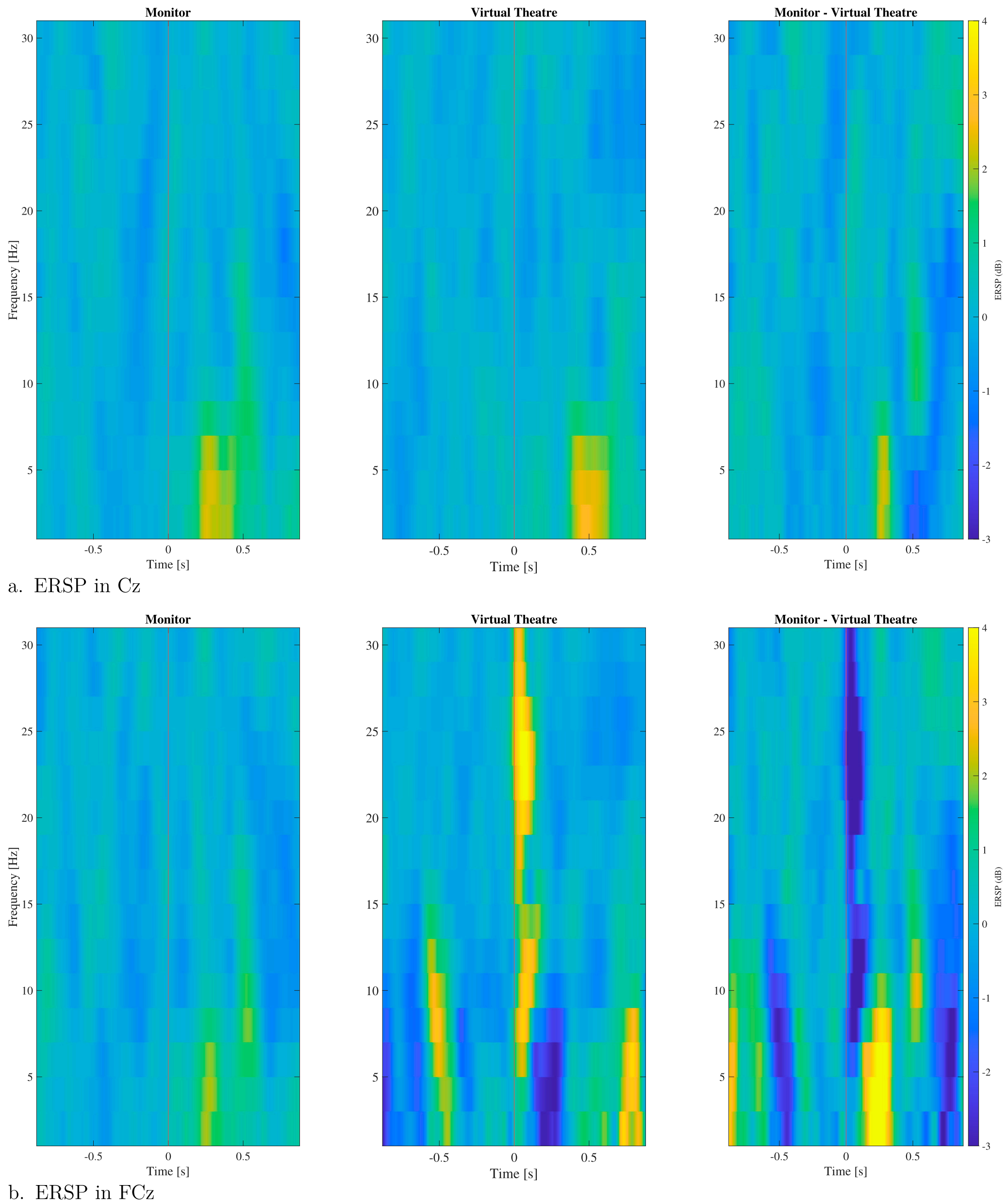

FIGURE 4
ERSP for electrodes Cz **(A)** and FCz **(B)** in the VT and Monitor environments and difference of the two environments. In the plot are reported just significant values along trials.

frequency bands. At 100 ms we can notice a higher desynchronization in the parietal zone for the Monitor environment, especially in the alpha band, while in the VT environment, this desynchronization is attenuated. At 300 ms in the Monitor environment, the expected spread activation in the fronto-central area is observed in both delta and theta bands. In contrast, no significant activity is observed in the VT environment. The brain's response to erroneous activity in the VT environment is more noticeable at 500 ms, where slight and more localized activity can be observed. In the Monitor environment, at the same instant, high activity is observed in the occipital regions, particularly concentrated in the alpha band. This type of activity is not evident in the VT environment, where significant activity cannot be detected after the typical response to the erroneous event.

Concerning the difference in the attentional state between the two environments, the violinplots showing significant differences for each considered attention related feature are reported in Figure 6. We can notice that for all features the Monitor stimulation resulted in a significantly higher attentional state if compared to the VT environment.

3.1.2 Classification performance

The performance of the LDA classifier in discriminating between ErrP and Non-ErrP epochs can be observed in both Monitor (blue) and VT (orange) environments for validation and

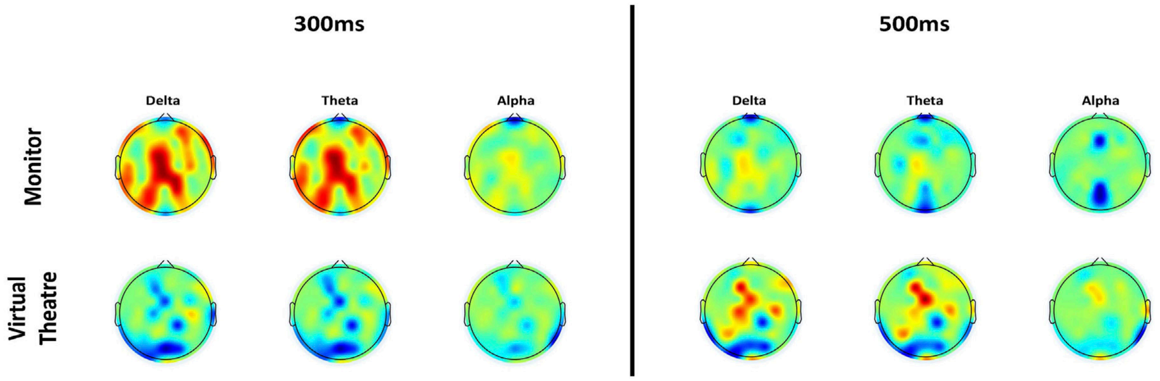

FIGURE 5
Topoplots of ERSP at 300 ms (left) and 500 ms (right) after the stimulus in Monitor and VT environments and in the δ, θ and α brain oscillations. In the plot are reported just significant values along trials.

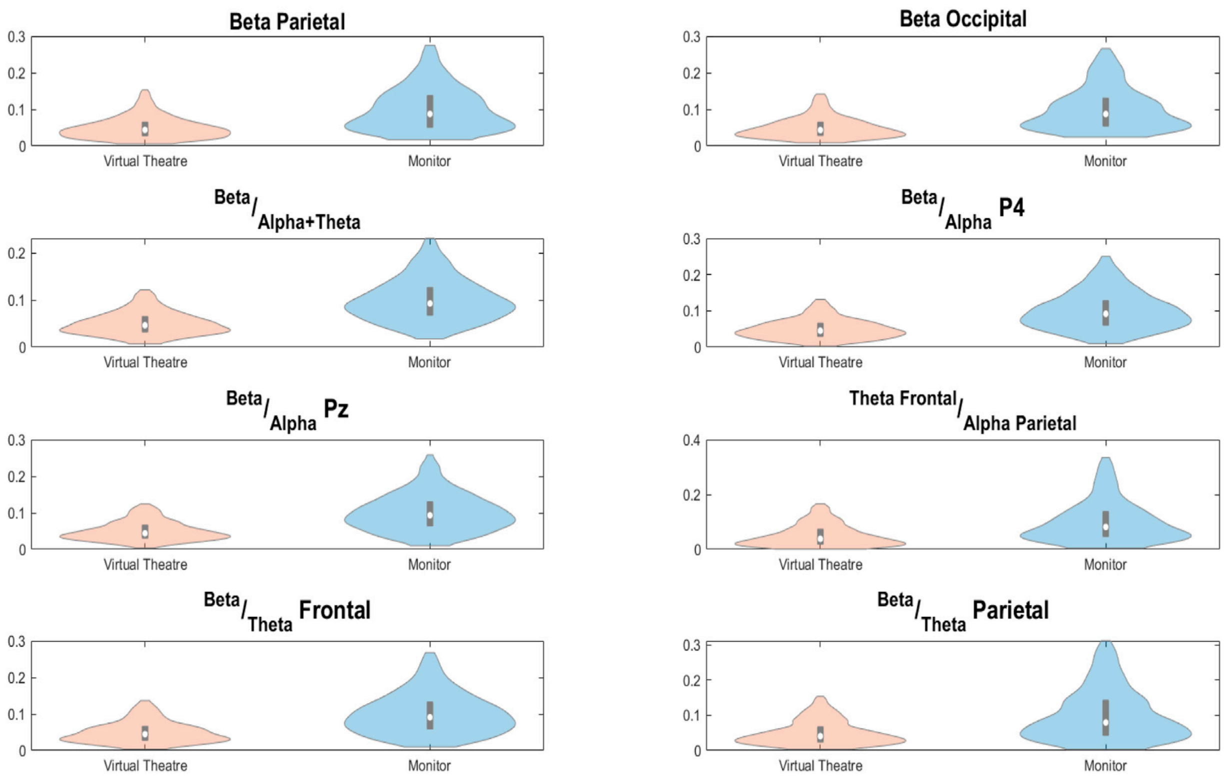

FIGURE 6
Distributions of examined attention related features for the VT (in orange) and the Monitor (in blue) environments.

test sets (*cf.* Figure 7). It is worth noticing that for all the considered metrics the Monitor environment results in better performance both in validation and test set. Moreover, the Monitor environment always resulted in performance over the 50% value, while the VT in balanced accuracy, precision and F1–score resulted in performance slightly above or below chance level (i.e., 50%).

3.2 Surprise effect on ErrP realization

The results presented for the two environment now will be presented for the two levels of probability of error happening (i.e.,: 20% and 50%). Also for this analysis the comparison have been made both in terms of neurophysiological response and performance in classification when distinguishing between ErrP and Non–ErrP events.

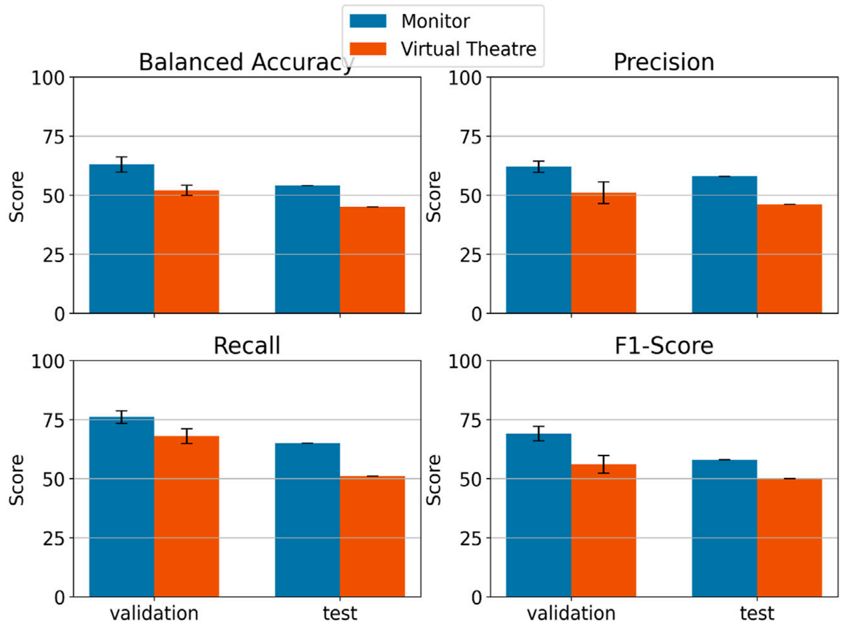

FIGURE 7
LDA classification performance in distinguishing between ErrP and Non−ErrP epochs using data coming from VT (in orange) and Monitor (in blue) environments. For validation set is reported the mean of the 5 folds cross validation and the standard deviation.

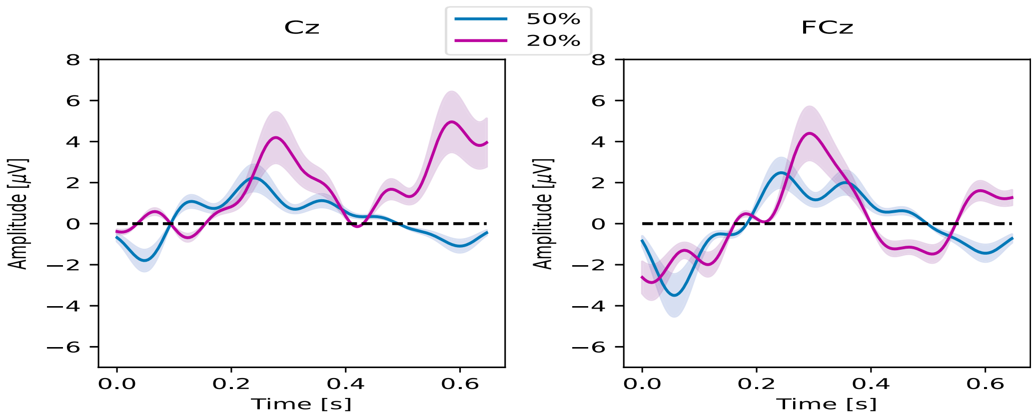

FIGURE 8
Grand Averages of ErrP trials for one subject in the 20% (in purple) and 50% (in blue) probability for electrodes Cz (left) and FCz (right) with the related confidence interval.

3.2.1 Neurophysiological response

Also when comparing the protocols with different probabilities of erroneous outcomes some differences can be noticed.

Illustrated in Figure 8, the ErrP Grand Average for one subject as an example, reveals the attainment of typical ErrP responses in both protocols across different surprise levels. Notably, the latencies of ErrP characteristic peaks for electrodes Cz (left) and FCz (right) approximate 300ms. However, qualitative distinctions in amplitude become evident, particularly pronounced when employing a probability of erroneous events at 20%.

Details of the ErrP characteristics in time and frequency domains for the single trials are reported in Figure 9. In particular from Figure 9A can be observed that significantly higher peaks, both positive and negative, are obtained in the protocol with a 20% probability of error, while no significant difference was found for the related latencies. Concerning the ErrP frequency domain features illustrated in Figure 9B, significant difference are reported only for the PSD computed in the θ band for both electrodes Cz and FCz.

The results of the time-frequency analysis in the two different protocols are reported as spectrograms in Figure 10 in terms of ERSP. Both for electrodes Cz and FCz no main differences are reported with a slightly more pronounced activation in the 20% protocol. These findings are confirmed by the ERSP topolots at 300 and 500 ms for the δ, θ and α bands depicted in Figure 5. At 300 m the level of activation is similar in both protocols with a more localized activity in the central area when using

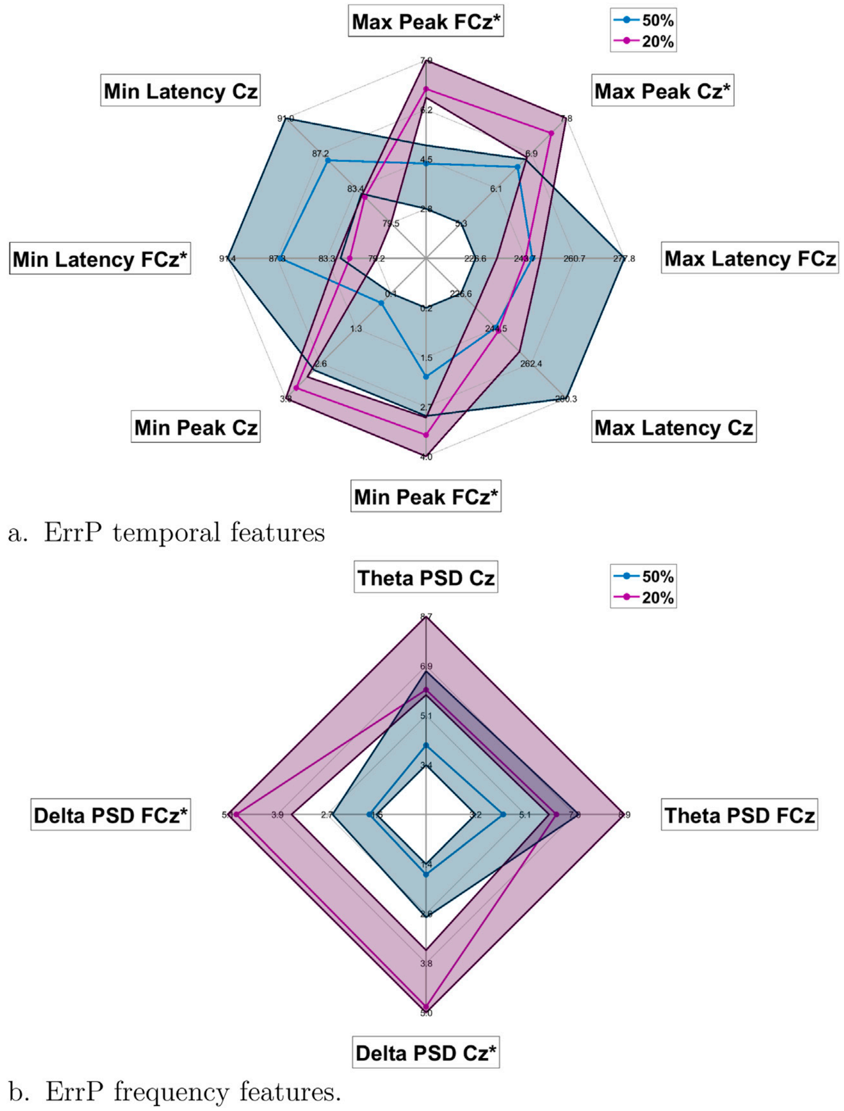

FIGURE 9
Radar plots of the temporal **(A)** and frequency **(B)** features for 20% probability of error events protocol (purple) and the 50% one (blue). For both classes and each feature is reported shaded the interquartile range.

a 20% of error probability. The desynchronization in the α band at 500 ms discussed in the previous section for the Monitor environment with 50% of error probability can be seen also for the 20% protocol (bottom left of Figure 11).

The analysis of the attention levels during the two protocols with different error probabilities is reported in Figure 12 using violin plots.

In this case, for all the attention–related features examined, when using a 20% of probability for erroneous events happening a significantly higher attention level can be appreciated if compared to the other protocol analyzed.

Table 2 reports the significant $(p - value < 0.01)$ Pearson correlations (corrected for multiple comparisons with the Bonferroni–Holm method) between ErrP and attention level characteristics for the protocol using a 20% probability of erroneous events, while no correlation has been found for all the other experimental setups. From a first analysis, it is observable that higher attentional states before the erroneous event yield to faster and more pronounced ErrP response.

3.2.2 Classification performance

Figure 13 displays the performance of an LDA classifier tasked with distinguishing between ErrP and Non-ErrP epochs in the context of the 20% error probability (depicted in blue) and the 50% probability (depicted in orange) protocols across validation and test sets.

It is noteworthy that, across all evaluated metrics, the 20% error probability protocol consistently yields superior performance in both validation and test sets. Specifically, the 20% error probability protocol consistently achieves performance surpassing the 75% threshold, whereas the 50% probability protocol demonstrates balanced accuracy, precision, and F1-score performance below 60% both in validation and test set.

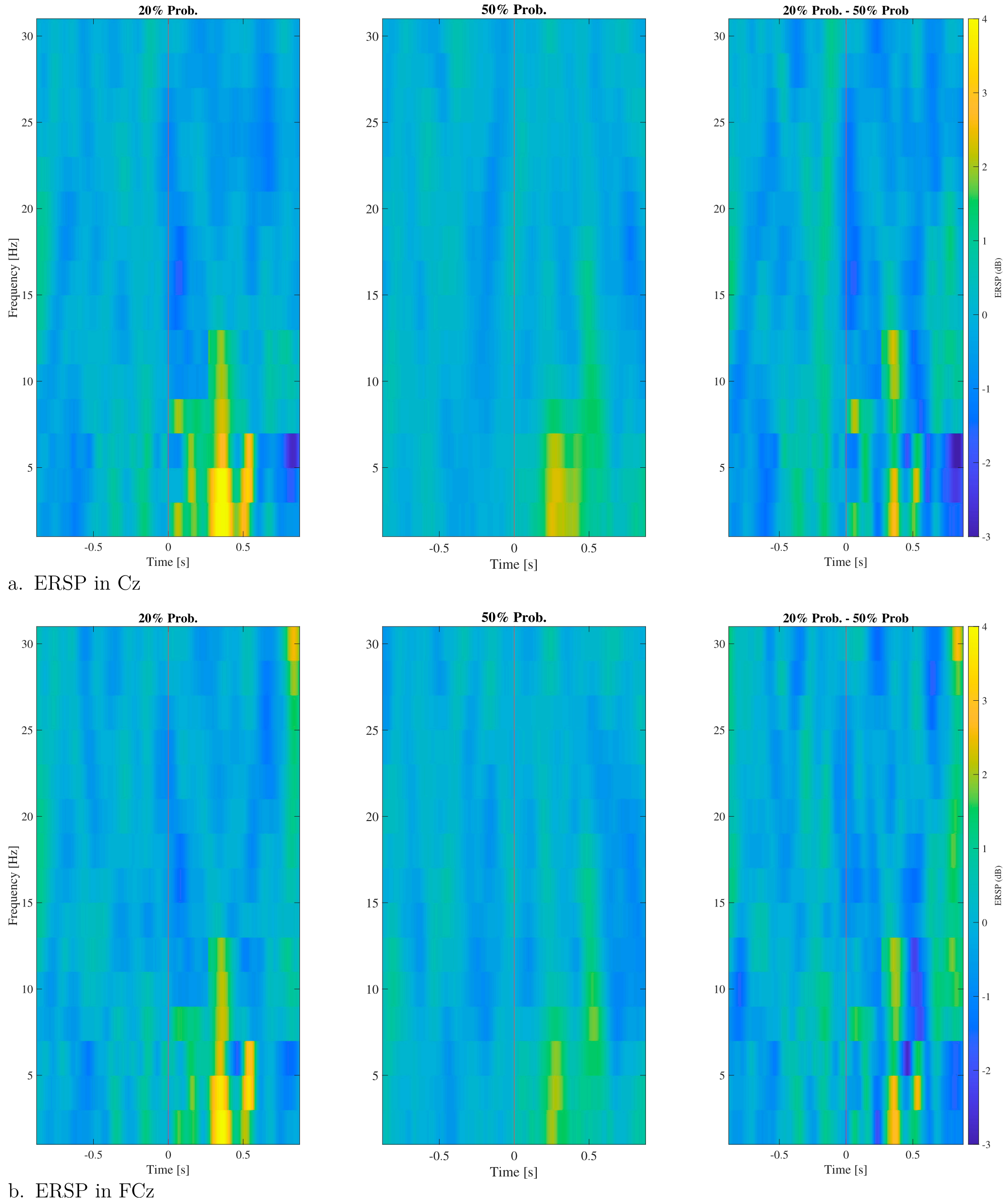

FIGURE 10
ERSP for electrodes Cz **(A)** and FCz **(B)** in the 20% probability of error events protocol and the 50% one and difference of the two environments. In the plot are reported just significant values along trials.

4 Discussions

In this paper, we examined two comparisons centered around the ErrP response and attention levels. The first of these comparisons analyzes the influence of the stimulation environment, specifically putting the Monitor environment against the VT setting in a within participants experimental design. Both environments utilized a crafted Unity stimulation protocol featuring a car-driving game where participants faced the prospect of missing targets. Remarkably, despite the correctness of the ErrP stimulation in both environments, distinctions emerged.

Within the Monitor environment, a discernibly higher amplitude of ErrP response unfolded across various dimensions: time, frequency, space, and time-frequency. This was accentuated by a faster and more pronounced response when compared to the VT environment. While these findings are preliminary due to our limited sample size the implications of this variance point towards the possibility that subjects, not used and untrained in the use of VR systems, may have exhibited different neural responses in these distinct environments. These results align with previous research investigating the relationship between VR usage and cognitive performance. While the literature shows some variability in results, several studies provide evidence

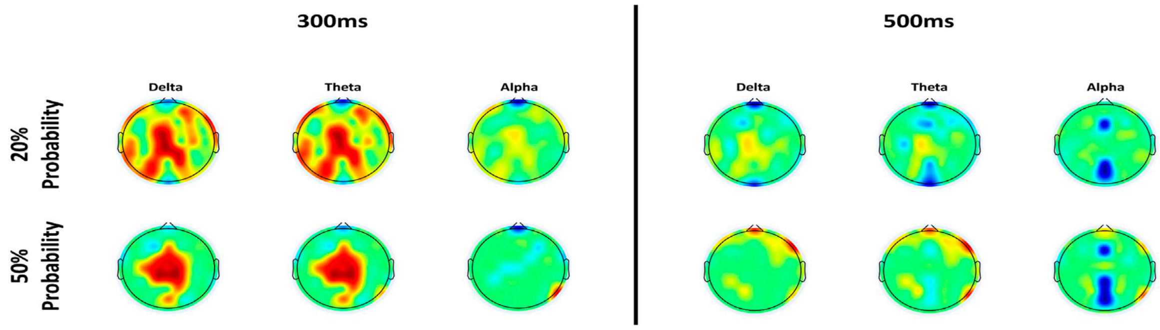

FIGURE 11
Topoplots of ERSP at 300 ms (left) and 500 ms (right) after the stimulus in the two protocols with different probability of error events and in the δ, θ and α brain oscillations. In the plot are reported just significant values along trials.

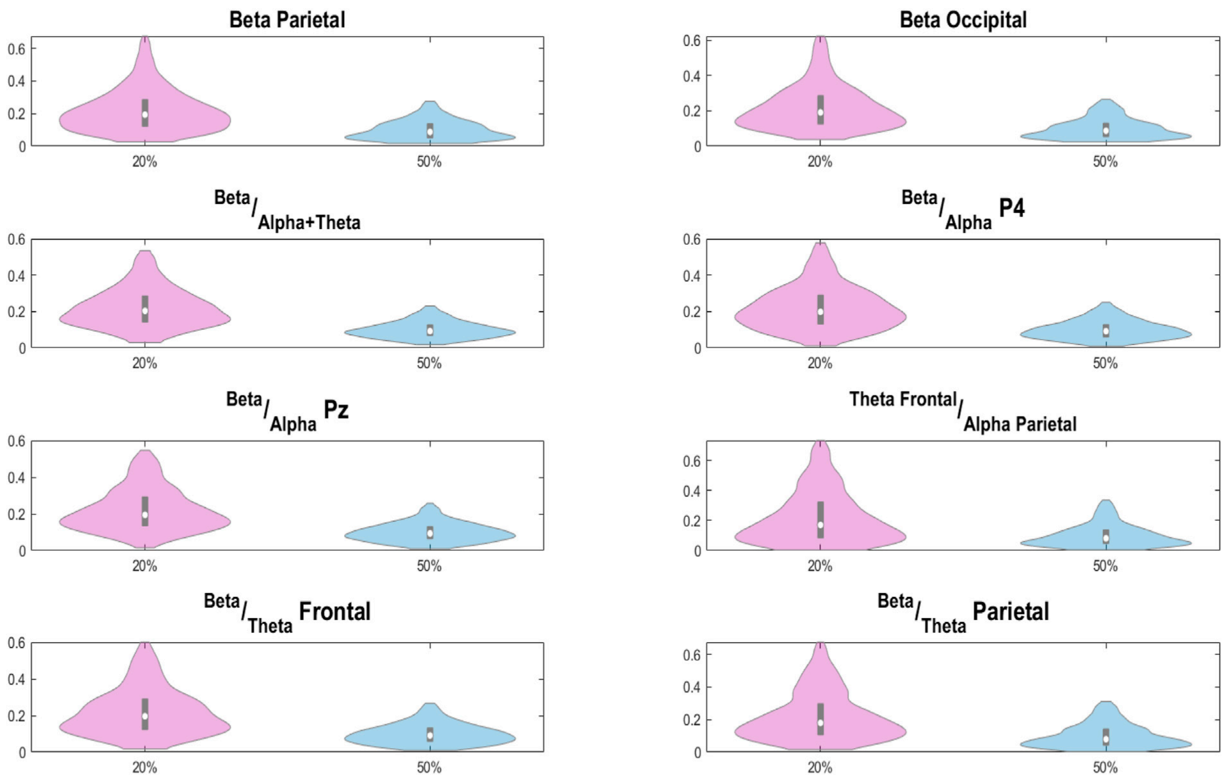

FIGURE 12
Distributions of examined attention related features for the 20% probability of error events protocol (in purple) and the 50% one (in blue).

supporting our observations. Notably, Szpak et al. (2019) demonstrated that VR environments can induce cognitive aftereffects independent of traditional cybersickness symptoms, leading to decreased task performance and increased reaction times. Similarly, Mittelstadt et al. (2019) observed that cognitive processing in VR environments can be compromised even in the absence of motion sickness or physical discomfort, suggesting that the cognitive load of virtual environments itself may influence task performance.

Moreover, the higher attention levels observed in the Monitor environment further underline the potential impact of subjects' unfamiliarity with VR systems on cognitive engagement. The hypothesis that participants were not habituated to VR experiences seems plausible as their attention-related features manifested differently in the Monitor environment. The application of an LDA classifier to discern between erroneous and correct events substantiated this trend, with the Monitor environment demonstrating better performance. This suggests that the ErrP characteristics captured in the Monitor environment were not only more robust but also more easily differentiable.

TABLE 2 Significant correlation values between ErrP characteristics and EEG attention–related features in the 20% protocol.

	Power ch P4 $\frac{\beta}{\alpha}$	Power ch pz $\frac{\beta}{\alpha}$	Power β parietal	Power β occipital	Power $\frac{\theta}{\alpha}$
ErrP PSD θ Cz	0.61	0.55	0.62	0.64	0.58
ErrP PSD δ Cz	0.58	0.54	0.60	0.61	0.59
ErrP Max Amplitude	0.71	0.68	0.64	0.61	0.62
ErrP Max Latency	−0.66	−0.65	−0.57	−0.48	−0.59

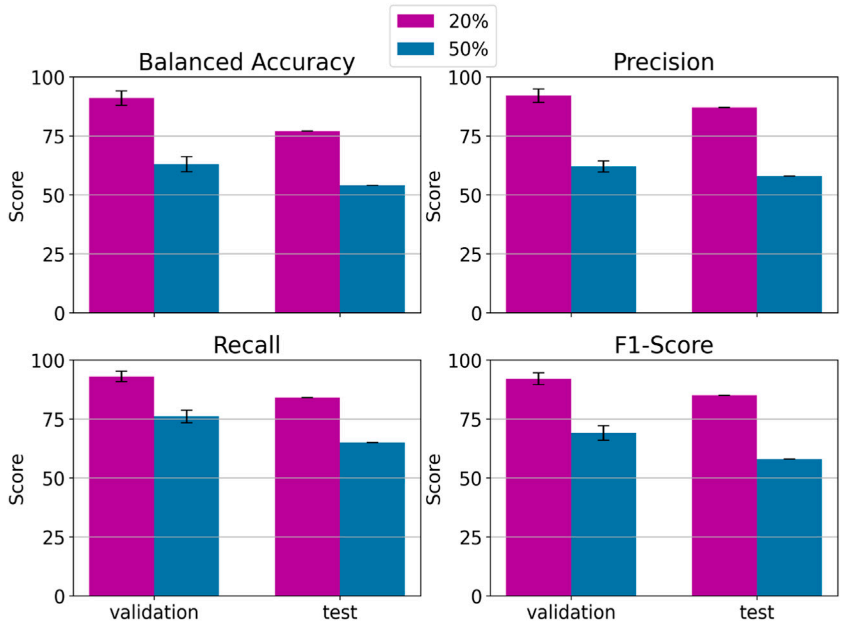

FIGURE 13
LDA classification performance in distinguishing between ErrP and Non–ErrP epochs using data coming from the 20% probability of error events protocol (in purple) and the 50% one (in blue). For validation set is reported the mean of the 5 folds cross validation and the standard deviation.

Moving to the second comparison, which scrutinized the impact of error probability, events with a 20% chance of error were juxtaposed against those with a 50% probability. Interestingly, the events with a lower probability of error displayed more pronounced ErrP characteristics, potentially indicating a heightened neural sensitivity to scenarios with a lower likelihood of error. Conversely, a significantly higher attention level was observed in events with a 20% probability of error, suggesting that the reduced probability of error might have increased participants' cognitive engagement. These results are consistent with previous evoked potential research using different paradigms. For instance, Verleger and Śmigasiewicz (2020) demonstrated that P300 amplitudes in visual and auditory tasks vary significantly with oddball probability.

The discovery of correlations between ErrP characteristics and specific attention features adds a layer of complexity to the relationship between ErrP and attention. Our analysis revealed significant positive correlations between the P300 amplitude of the ErrP response and sustained attention metrics, suggesting that stronger error detection mechanisms may be associated with enhanced attentional resources. Additionally, we observed a noteworthy negative relationship between the error-related negativity (ERN) latency and attention switching capacity. These findings align with previous research by Klimesch (2014), who demonstrated that attention-related oscillatory activity can modulate error processing mechanisms. Similarly, Datta et al. (2017) found that variations in attention levels can significantly impact the amplitude and timing of error-related potentials.

Our findings have particular relevance for the design and implementation of AR/VR protocols aimed at cognitive state stimulation. The observed differences in attention and ErrP responses between monitor and VR environments suggest that careful consideration must be given to the choice of interface when designing cognitive training or assessment protocols. The potential impact of environmental familiarity on cognitive engagement indicates that AR/VR protocols may need to incorporate adaptation periods or account for individual differences in technology experience.

Future studies would benefit significantly from incorporating standardized psychological attention assessments to provide a more comprehensive understanding of attentional processes. The Test of Variables of Attention (TOVA) Braverman et al. (2010) could offer valuable insights into sustained attention and response inhibition, while the Attention Network Test (ANT) Fan et al. (2002) would help differentiate between alerting, orienting, and executive attention networks. Additionally, the Multiple Object Tracking (MOT) paradigm Cavanagh and Alvarez (2005) could provide crucial data about divided attention capabilities in virtual environments. These established measures would complement our EEG-based attention metrics and potentially reveal how different aspects of attention interact with error processing in various virtual environments.

5 Conclusion

In conclusion, these dual comparisons highlight the interplay between stimulation environments, error probabilities, ErrP responses, and attention levels. The intricate nuances uncovered in these experiments underscore the importance of carefully considering these factors when designing experimental protocols and interpreting results, particularly in the dynamic realms of BCIs and virtual reality applications. Further research and in-depth analyses will undoubtedly contribute to a more comprehensive understanding of the interdependencies within these neural and cognitive phenomena.

Despite the promising findings, it is essential to acknowledge the limitations of our study. The relatively small sample size necessitates cautious interpretation of our results, and replication with larger populations is needed to validate these findings. Moreover, we only examined two specific environments, and additional research is needed to generalize these findings to other settings. Future studies could explore the potential benefits and drawbacks of various AR/VR environments and their effects on the ErrP response and attentional processes.

Our findings have significant implications for the development of AR/VR-based cognitive training protocols and therapeutic interventions. The observed relationship between environmental factors and cognitive responses suggests that careful attention must be paid to the design of virtual environments to optimize cognitive engagement and learning outcomes. Future research should focus on establishing standardized protocols for assessing attention and error processing in virtual environments, potentially incorporating multiple attention assessment tools to capture different aspects of cognitive function. This multi-modal approach would provide a more comprehensive understanding of how virtual environments influence cognitive processing and could lead to more effective and personalized AR/VR interventions.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving humans were approved by the Ethics Committee of Politecnico di Milano. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study. Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

Author contributions

AF: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Software, Writing–original draft, Writing–review and editing. LM: Conceptualization, Data curation, Formal Analysis, Investigation, Supervision, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

References

Bacigalupo, F., and Luck, S. J. (2019). Lateralized suppression of alpha-band eeg activity as a mechanism of target processing. *J. Neurosci.* 39, 900–917. doi:10.1523/JNEUROSCI.0183-18.2018

Barry, R. J., Clarke, A. R., and Johnstone, S. J. (2003). A review of electrophysiology in attention-deficit/hyperactivity disorder: I. qualitative and quantitative electroencephalography. *Clin. Neurophysiol.* 114, 171–183. doi:10.1016/S1388-2457(02)00362-0

Braboszcz, C., and Delorme, A. (2010). Lost in thoughts: neural markers of low alertness during mind wandering. *NeuroImage* 54, 3040–3047. doi:10.1016/j.neuroimage.2010.10.008

Braverman, E., Chen, A., Chen, T., Schoolfield, J., Notaro, A., Braverman, D., et al. (2010). Test of variables of attention (TOVA) as a predictor of early attention complaints, an antecedent to dementia. *Neuropsychiatr. Dis. Treat.* 6, 681–90. doi:10.2147/NDT.S12243

Buttfield, A., Ferrez, P. W., del, R., and Millan, J. (2006). Towards a robust bci: error potentials and online learning. *IEEE Trans. Neural Syst. Rehabilitation Eng.* 14, 164–168. doi:10.1109/tnsre.2006.875555

Cavanagh, P., and Alvarez, G. A. (2005). Tracking multiple targets with multifocal attention. *Trends Cognitive Sci.* 9, 349–354. doi:10.1016/j.tics.2005.05.009

Chavarriaga, R., del, R., and Millan, J. (2010). Learning from eeg error-related potentials in non invasive brain-computer interfaces. *IEEE Trans. Neural Syst. Rehabilitation Eng.* 18, 381–388. doi:10.1109/tnsre.2010.2053387

Clayton, M. S., Yeung, N., and Cohen Kadosh, R. (2018). The roles of cortical oscillations in sustained attention. *Trends Cognitive Sci.* 22, 347–356. doi:10.1016/j.tics.2018.02.004

Dal Seno, B., Matteucci, M., and Mainardi, L. (2010). Online detection of p300 and error potentials in a bci speller. *Comput. Intell. Neurosci.* 2010, 1–5. doi:10.1155/2010/307254

Datta, A., Cusack, R., Hawkins, K., Heutink, J., Rorden, C., Robertson, I. H., et al. (2017). The p300 as a marker of waning attention and error propensity. *Comput. Intell. Neurosci.* 2017, 3409749. doi:10.1155/2017/3409749

De Venuto, D., and Mezzina, G. (2021). A single-trial p300 detector based on symbolized eeg and autoencoded-(1d)cnn to improve itr performance in bcis. *Sensors* 21, 3961. doi:10.3390/s21123961

Duffy, F. H., Burchfiel, J. L., and Lombroso, C. T. (1979). Brain electrical activity mapping (beam): a method for extending the clinical utility of eeg and evoked potential data. *Ann. Neurology* 5, 309–321. doi:10.1002/ana.410050402

Falkenstein, M., Hohnsbein, J., and Hoormann, J. (1995). Event-related potential correlates of errors in reaction tasks. *Electroencephalogr. Clin. neurophysiology. Suppl.* 44, 287–296.

Falkenstein, M., Hoormann, J., Christ, S., and Hohnsbein, J. (2000). Erp components on reaction errors and their functional significance: a tutorial. *Biol. Psychol.* 51, 87–107. doi:10.1016/s0301-0511(99)00031-9

Fan, J., McCandliss, B. D., Sommer, T., Raz, A., and Posner, M. I. (2002). Testing the efficiency and independence of attentional networks. *J. Cognitive Neurosci.* 14, 340–347. doi:10.1162/089892902317361886

Farabbi, A., Aloia, V., and Mainardi, L. (2022). Arx-based eeg data balancing for error potential bci. *J. Neural Eng.* 19, 036023. doi:10.1088/1741-2552/ac6d7f

Farabbi, A., and Mainardi, L. (2022). Eeg analysis of selective attention during error potential bci experiments. *2022 IEEE 21st Mediterranean Electrotechnical Conference (MELECON)* 420–423. doi:10.1109/MELECON53508.2022.9842955

Feng, L., Xiaoyu, L., Fei, W., Deng Yong, Z., Yi, X., and Yi, H. (2020). A novel P300 classification algorithm based on a principal component analysis-convolutional neural network. *Appl. Sci.* 10, 1546. doi:10.3390/app10041546

Ferrez, P., del, R., and Millan, J. (2008). Error-related eeg potentials generated during simulated brain-computer interaction. *IEEE Trans. bio-medical Eng.* 55, 923–929. doi:10.1109/tbme.2007.908083

Fu, Z., Sajad, A., Errington, S. P., Schall, J. D., and Rutishauser, U. (2023). Neurophysiological mechanisms of error monitoring in human and non-human primates. *Nat. Rev. Neurosci.* 24, 153–172. doi:10.1038/s41583-022-00670-w

Gehring, W. J., and Fencsik, D. E. (2001). Functions of the medial frontal cortex in the processing of conflict and errors. *J. Neurosci.* 21, 9430–9437. doi:10.1523/JNEUROSCI.21-23-09430.2001

Gola, M., Magnuski, M., Szumska, I., and Wrobel, A. (2013). Eeg beta band activity is related to attention and attentional deficits in the visual performance of elderly subjects. *Int. J. Psychophysiol.* 89, 334–341. doi:10.1016/j.ijpsycho.2013.05.007

Hajcak, G., McDonald, N., and Simons, R. (2003). To err is autonomic: error-related brain potentials, ans activity, and post-error compensatory behavior. *Psychophysiology* 40, 895–903. doi:10.1111/1469-8986.00107

Ke, J., Zhang, M., Luo, X., and Chen, J. (2021). Monitoring distraction of construction workers caused by noise using a wearable electroencephalography (eeg) device. *Automation Constr.* 125, 103598. doi:10.1016/j.autcon.2021.103598

Klimesch, W. (2014). Alpha-band oscillations, attention, and controlled access to stored information. *Trends Cognitive Sci.* 18, 606–617. doi:10.1016/j.tics.2012.10.007

Lotte, F., Bougrain, L., Chichokia, A., Clerk, M., Congedo, M., Rakotomamonjy, A., et al. (2018). A review of classification algorithms for eeg-based brain–computer interfaces: a 10 year update. *J. Neural Eng.* 15, 031005. doi:10.1088/1741-2552/aab2f2

Lutsyuk, N., Eismont, E., and Pavlenko, V. (2006). Correlation of the characteristics of eeg potentials with the indices of attention in 12-to 13-year-old children. *Neurophysiology* 38, 209–216. doi:10.1007/s11062-006-0048-4

Makeig, S. (1993). Auditory event-related dynamics of the eeg spectrum and effects of exposure to tones. *Electroencephalogr. Clin. Neurophysiology* 86, 283–293. doi:10.1016/0013-4694(93)90110-H

Michel, C. M., and Murray, M. M. (2012). Towards the utilization of eeg as a brain imaging tool. *Neuroimage* 61, 371–385. doi:10.1016/j.neuroimage.2011.12.039

Mittelstadt, J., Wacker, J., and Stelling, D. (2019). Vr aftereffect and the relation of cybersickness and cognitive performance. *Virtual Real.* 23, 143–154. doi:10.1007/s10055-018-0370-3

Ogrim, G., Kropotov, J., and Hestad, K. (2012). The quantitative eeg theta/beta ratio in attention deficit/hyperactivity disorder and normal controls: sensitivity, specificity, and behavioral correlates. *Psychiatry Res.* 198, 482–488. doi:10.1016/j.psychres.2011.12.041

Ranta-aho, P., Koistinen, A., and Ollikainen, J. (2003). Subspace regularization method for the single trial estimation of multi channel evoked potential measurements. *IEEE Trans. Biomed. Eng.* 46, 1–9. doi:10.1109/TBME.2002.807654

Škola, F., and Liarokapis, F. (2018). Embodied vr environment facilitates motor imagery brain–computer interface training. *Comput. Graph. (Pergamon)* 75, 59–71. doi:10.1016/j.cag.2018.05.024

Spuler, M., Bensch, M., Kleih, S., Rosenstiel, W., Bogdan, M., and Kubler, A. (2012). Online use of error-related potentials in healthy users and people with severe motor impairment increases performance of a P300-BCI. *Clin. Neurophysiol.* 123, 1328–1337. doi:10.1016/j.clinph.2011.11.082

Szpak, A., Michalski, S. C., Saredakis, D., Chen, C. S., and Loetscher, T. (2019). Beyond feeling sick: the visual and cognitive aftereffects of virtual reality. *IEEE Access* 7, 130883–130892. doi:10.1109/ACCESS.2019.2940073

Vauhkonen, M., Vadasz, D., Karjalainen, P. A., Somersalo, E., and Kaipio, J. P. (1998). Tikhonov regularization and prior information in electrical impedance tomography. *IEEE Trans. Med. Imaging* 17, 285–293. doi:10.1109/42.700740

Verleger, R., and Śmigasiewicz, K. (2020). Effects of relevance and response frequency on p3b amplitudes: review of findings and comparison of hypotheses about the process reflected by p3b. *Psychophysiology* 57, e13542. doi:10.1111/psyp.13542

Vourvopoulos, A., Pardo, O. M., Lefebvre, S., Neureither, M., Saldana, D., Jahng, E., et al. (2019). Effects of a brain-computer interface with virtual reality (vr) neurofeedback: a pilot study in chronic stroke patients. *Front. Hum. Neurosci.* 13, 210. doi:10.3389/fnhum.2019.00210

Wolpaw, J. R., Birbaumer, N., Heetderks, W. J., McFarland, D. J., Peckham, P. H., Schalk, G., et al. (2000). Brain-computer interface technology: a review of the first international meeting. *IEEE Trans. Rehabilitation Eng.* 8, 164–173. doi:10.1109/tre.2000.847807