Evaluating Memory and Cognition via a Wearable EEG System: A Preliminary Study

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Abstract. Human memory comprises one of the most complex brain functions, attracting researchers to unveil the neural mechanisms governing its effective operation. In this respect, the current study examines the application of a wearable single-channel EEG to the interpretation of cognitive operations reflecting memory processes. For this purpose, we implemented a set of tasks for evaluating the participants' processing skills and memory efficiency, in order to examine potential outcomes derived from a specialized cognitive training routine. The employed training method targeted the distinction of automatic and controlled processing and its effects on memory, while we also investigated transfer effects to untrained tasks. Based on the electrophysiological data recorded during the cognitive tasks, we computed measures of induced EEG activity for each frequency band to examine the influence of cognitive training on both task performance and brain activity, as well as whether the EEG metrics could provide insight into the underlying brain processes and augment the interpretation of behavioral outcomes. Ultimately, statistical analysis showed an apparent contribution of EEG in understanding the observed behavioral differences, while our training program had a clear impact on the participants' performance and brain activity. Moreover, we observed the reported distinction between automatic and controlled memory processes which play an integral part in both ageing and cognitive impairments.

Keywords: Memory · Cognitive training · Electroencephalography · Portable EEG · EEG synchronization · Dual process theory

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1 Introduction

The human brain is one of the most complicated organs of the human body, working round the clock engaging with stimulus processing and activity coordination [1]. It comprises multiple interconnected units that both specialize in specific functions (e.g. vision) and work collectively in order to serve more convoluted operations such as speech, motion and problem solving. This category also includes memory processes, which have drawn intensive research interest due to the variety of cognitive processes involved (stimulus processing, encoding, storage, consolidation, retrieval) as well as their immense influence on one's personality [2].

In this context, numerous studies have investigated the causes and underlying mechanisms of cognitive decline, focusing on the effects of age and cognitive disorders. To that end, both healthy and cognitively impaired individuals have been recruited in multiple experiments involving the completion of cognitive tasks that gauge cognitive capacity and overall skills [3, 4]. Moreover, a multitude of research works have attempted to implement non-pharmacological interventions in pursuance of maintaining or even restoring cognitive functionality [5, 6]. Indeed, the human brain has been found to behave much like a muscle, in a sense that it can be trained in order to "stay in shape" or even improve its performance [7, 8].

From this standpoint, cognitive training has been implemented for maintaining or improving cognitive capacity and processing skills, as well as for slowing down or even mitigating the effects of age-related or impairment-related decline [7, 9]. For this purpose, researchers have aimed at capitalizing on processes that normally do not diminish with age and remain intact until the last stages of most cognitive disorders. In that spirit, we opted to focus on the distinction between controlled and automatic processing, as described by the dual process theory [10–12]. Specifically, automatic processing is a fast, unconscious and stimulus-driven operation, while controlled processes are conscious and demand more resources, deteriorating with age or under the presence of a cognitive impairment. In addition, on investigating cognitive training outcomes, researchers often analyze potential transfer effects [13], namely performance differences observed in other tasks, closely (near transfer) or remotely (far transfer) related to the trained task.

On studying the above phenomena, electroencephalography (EEG) has emerged as an invaluable tool, since it provides access to physiological activity reflecting cognitive processes, enabling scientists to extract measurable – and therefore objective – information with respect to brain functions [14]. However, high-density recordings employ large-scale devices under laboratory settings, requiring time-demanding setups that lack portability and convenience for the people involved. On that premise, the availability of wearable non-invasive EEG recording devices [15] has allowed their easy application on cognition analyses, greatly augmenting the interpretation of behavioral outcomes [16]. Within this context, we developed a dedicated experimental protocol for assessing cognitive training effects on memory and processing functions based on a combination of EEG-related features and conventional behavioral metrics. In particular, we sought to examine aspects of face-name memory related to familiarity and recollection processes that bear a major role in the study of ageing and dementia effects [17] using a single-channel dry EEG with high portability and user-friendly setup. Considering the fact that very few studies have targeted the EEG aspect of training effects based on dual process theory, our primary goal was to establish the applicability of minimal wearable EEG in studying cognitive training outcomes, as well as to assess the effects of the implemented training routine on brain functions.

2 Materials and Methods

2.1 Participants

Data were acquired from six healthy adults (4 male, 2 female) aged 25–40 years old with homogeneous educational level. All participants were right-handed and reported no history of cognitive disorders or medication intake, as well as normal amount of sleep for two days prior to the experiment. During the pre-experimental screening process, they all scored over 28 at the Montreal Cognitive Assessment (MoCA) [18]. The study was conducted in accordance with the Declaration of Helsinki, while written informed consent was obtained from all individuals.

2.2 Experimental Design

The participants were divided into two groups (training group and control group, each group consisting of two men and one woman) and were requested to complete a series of memory related cognitive tasks, during which they were placed in front of a TV monitor at a distance of 2 m. The experimental protocol (Fig. 1) consisted of three stages, conducted over a 6-day period. During the first stage (pre-training evaluation), the participants were asked to complete a baseline evaluation consisting of a Face-Name Memory (FNM) Test, the Verbal Paired Associates (VBA) Test [19] and an N-back task [20]. During the second stage, beginning from the following day, the training group underwent a 4-day training program involving an application of the Repetition-Lag Procedure [21–23] for two sessions per day. On the 6th day, a post-training evaluation (3rd stage) took place, where both groups had to repeat the pre-training evaluation tasks. The control group completed only the pre-training and post-training stages, while participants from both groups were asked to not perform any further cognitive exercises (e.g. crosswords) during the 4-day interval between the two evaluation stages.

Single-channel EEG data were recorded during the pre- and post-training stages for all participants, while no recording was conducted during training in an attempt to establish a comfortable training environment. For every task, each trial (stimulus presentation & response intervals) followed a 5-s time interval, representing the reference interval corresponding to baseline EEG activity. In order to avoid overextending the duration of the evaluation stages, we limited the number of trials close to the minimum required based on literature [24, 25], leading to a total duration of approximately 65 min, including three 3-min breaks between two consecutive tasks.

The FNM test comprised the main cognitive task of the experiment, gauging the participants' skills on face recognition and name recall, while the VBA test and the N-back task were employed for examining transfer effects of training, assessing verbal and working memory respectively. Our hypothesis was that the VBA test would reflect near transfer, while the N-back task would reveal potential far transfer effects. Training was conducted using the repetition-lag procedure, focusing on separating automatic and controlled memory processes and strengthening the latter, which are known to decline due to age and cognitive impairment. Finally, it must be emphasized that participants were strongly advised to use the same mnemonic strategy during each task for all sessions (pre-training & post-training), in order to avoid performance differences due to strategy effectiveness.

The 380 images used for the face recognition tasks (FNM & repetition-lag training) were acquired from the FERET, PICS and IMM databases, selecting pictures with neutral facial expressions and no accessories (e.g. glasses or hats), while maintaining a uniform age distribution and a unit ratio of males and females. All images were normalized regarding their dimensions and were converted to grayscale and jpg format. The names that were matched with the faces were derived based on the results of the survey given in [26], consisting of the most frequent male and female names.

Face-Name Memory Test. Our FNM test involved two sessions of a study phase and an immediate recognition phase, as well as a delayed recognition phase. During the study phase, each participant was presented with a series of 15 face-name combinations, which comprised the study list. This step was directly followed by the immediate recognition phase (after 20 s), involving a series of 30 recognition tasks featuring the 15 studied faces and 15 new faces (distractors). On each task, the participant was presented with a face and was asked to respond on whether or not it was part of the study list. Upon a positive response (correct or not) the participant had to also provide a name to match with the face. After each recognition task, visual feedback was provided on the response correctness. Subsequently, after time delay of 20 min, participants again completed a series of recognition tasks with the same stimuli, which corresponded to a delayed recognition phase, during which no response feedback was provided. Based on the respective time windows after the study phase, the immediate and delayed recognition phases were expected to evaluate short-term and long-term memory. The stimuli presentation order was defined pseudorandomly and each stimulus was presented for 5 s followed by a 5-s interstimulus interval, while the response was to be provided within 4 s.

Verbal Paired Associates Test. Similar to the FMN test, the VBA test included two sessions of a study phase and an immediate recall phase, followed by a delayed recognition phase. Instead of faces, the stimuli for this test consisted of word pairs presented on the screen. During a study phase, the participants were presented with a sequence of 15 word pairs (study list), the two words being semantically unrelated and displayed aside one another. Afterwards, during the immediate recall phase, the first (left) word of each pair was shown (representing the cue) and the participant was asked to voice the second word (cued recall), followed by an acoustic feedback. It is noted that only the left word of each pair was given as a cue, corresponding to the priming condition for the VBA test [27]. Twenty minutes after the two sessions of study and immediate recall, a delayed recognition phase was conducted where 45 word pairs were presented and the individuals were asked to recognize whether they were part of the study list. No response feedback was provided. The additional (non-study) word pairs were formed by mixing the original word pairs, teaming the first word of each pair with the second word of another. The stimuli presentation order was pseudorandom and each stimulus was presented for 4 s followed by a 5-s interstimulus interval, while the response was to be provided within 4 s.

N-back Task. During the N-back task, the participants were presented with a sequence of digits, while for each stimulus they had to respond within 2 s on whether this specific digit appeared exactly N positions earlier in the sequence. Thereby, before each new stimulus they had to remember the latest N digits, where the N value echoed the difficulty level of the task. In the current study, we examined 3 distinct difficulty levels ($N_1 = 2$, $N_2 = 3$, $N_3 = 4$) that included 12, 13 and 14 trials for each level respectively. The interstimulus interval was set at 3 s, with 5-s and 20-s intervals between levels and sessions respectively. The digits for each sequence were determined pseudorandomly, ensuring that each N-back level contained at least 4 digit repetitions. Each set of the three difficulty levels was conducted three times and no response feedback was provided.

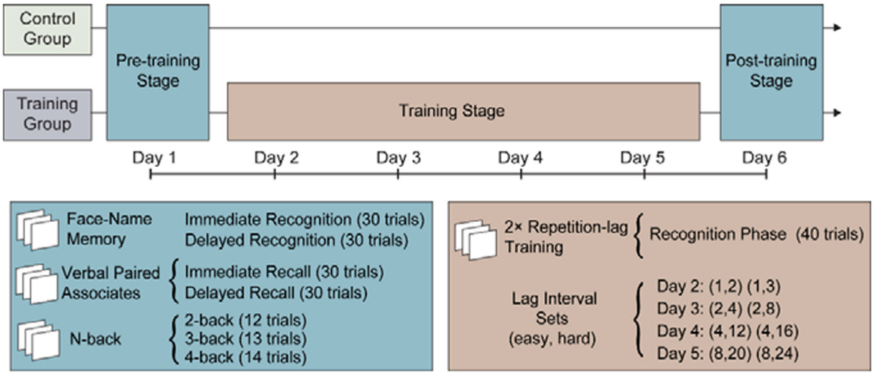

Fig. 1. Experimental Protocol. On the upper part of the figure the three protocol stages are displayed, relative to their duration and group participation. The bottom part depicts the specific tasks of the pre- and post-training stages (left) as well as the training stage (right).

Repetition-Lag Training. For the training method selection, the criteria used by the authors required a relatively uncomplicated method without a steep learning curve that presented relevance with our targeted cognitive processes, namely face recognition and name recall. In addition, we sought a method promoting implicit learning, presenting a record of successful applications as per existing studies. Based on these criteria, we decided to adopt the repetition-lag procedure (adjusted for face recognition), which builds on the dual process theory described in the "Introduction" section.

Each session of the repetition-lag procedure consisted of a study phase and a recognition phase. During the study phase, the participant was presented with a series of 16 study faces and a corresponding name, comprising the study list, which was displayed twice. Each stimulus was presented for 5 s, while the interstimulus interval was set at 5 s. After 1 min the recognition phase was carried out, where each individual was subjected to a series of yes/no recognition tasks. More specifically, we presented a list of faces (without a name) and the participants were to decide (within a response time of 3 s) whether a face belonged to the original study list or not. Whenever a face was recognized, the individual was also asked to provide a name to match with the face (within 5 s), thus completing the face-name recognition. After each recognition task, the individual was provided with visual feedback on whether the responses on face recognition and name recall were correct or incorrect.

However, some of the non-study faces were presented more than once, in an attempt to lure the individual into falsely recognizing them as parts of the study list, failing to recollect that they have indeed seen them before, although not among the study faces they were expected to "learn". These 16 faces were part of the repetition list, while the interval between two consecutive presentations of a repetition item represented the lag interval. The lag interval corresponded to the difficulty level of the recognition phase, since the more items that intervene between two presentations of the same face, the harder it was for the participants to recognize whether they saw this specific face earlier during the recognition phase or as part of the study list. Indicatively, it has been reported that a healthy young adult can achieve lags of about 18–19 [28]. Finally, the recognition phase included 8 additional faces that belonged neither to the study list nor to the repetition list, hence presented only once during the recognition phase, composed the filler list. Therefore, the recognition phase involved a total of 40 trials. If no more than two recognition errors were committed, the lag interval was increased for the next session, which was therefore carried out at a higher difficulty level. Otherwise, the lag interval remains the same for the next session, until the target criterion is met. The basic version of the repetition-lag procedure employs a single lag interval for each session, however some researchers have opted for a set of two lag interval values, both fixed for each session [28]. For the purposes of this study we have adopted the second approach, defining sets of two lag interval values ("easy" and "hard"). In that way, a participant could simultaneously practice with the two values during each session, where the easy value reflects the performance level achieved through the previous session and the hard value represents the elevated new practice level. It should be noted that name recall errors did not impact level progression, as only face recognition errors were taken into account for increasing the lag intervals of the next session. The lag interval sets that were used in this study were based on the research by [28], thus for our 4-day, 2 session-per-day training program we used the following eight sets: (1, 2), (1, 3), (2, 4), (2, 8), (4, 12), (4, 16), (8, 20), (8, 24). Furthermore, every session employed a different study list in order to avoid "learning" faces and instead trigger overall strengthening of face-name encoding and recognition cognitive processes.

The distinctiveness of this procedure in introducing non-target items presented more than once during recognition enables the dissociation of familiarity and recollection memory processes, rendering the method particularly intriguing for the authors. Specifically, each face that is part either of the study list or the repetition lists triggers an automatic familiarity effect to the individual, who has already been presented with this specific face. However, the participant has then to recall the learning context for this face, meaning to remember whether it was presented as a study face or not. This function represents recollection, which has been identified as part of controlled processing, known to decline due to age or cognitive impairment. In conclusion, by receiving feedback on correct/incorrect responses and progressively increasing difficulty, it has been hypothesized that the individuals implicitly (i.e. implicit learning) work on improving their controlled processing skills and therefore their ability to recall contextual information when recognizing familiar faces.

2.3 Data Acquisition and Pre-processing

Physiological recordings were conducted using the MindWave Mobile [29–31], a single-channel wearable EEG device with an Fp1 dry sensor and a reference A1 sensor, able to record 12-bit signals of up to 100 Hz with a sampling rate of 512 Hz. For the purposes of our study we used custom codes developed in MATLAB R2017b using the *EEGLAB* toolbox. For establishing connectivity between MindWave Mobile and MATLAB we used the necessary files provided in [32] as well as the recommended compiler from [33]. The experiment was conducted using two concurrent MATLAB sessions synced with each other, one handling EEG recordings and the other administering the computerized protocol, managing behavioral data and creating the appropriate event markers for the EEG data processing.

Initially, the raw EEG data recorded during the pre-training and post-training stages of the study were band-pass filtered by applying a windowed sinc FIR filter using a Blackman window with a bandwidth of 0.7–40.0 Hz. Subsequently, data were detrended before undergoing a denoising process. Specifically, due to the single-channel recording device, we employed EMD-ICA [34] in order to isolate noisy signal components and reconstruct the original EEG signal using only the desired components. According to this method, we firstly applied Empirical Mode Decomposition (EMD) using the *EMD-LAB* extension of the EEGLAB toolbox [35] in order to separate the one-dimensional EEG signal into four components, constituting the Intrinsic Mode Functions (IMFs). The generated IMFs represent oscillations within the source signal and are by default sorted based on their periodicity and decreasing frequency content. Afterwards, Independent Component Analysis (ICA) was applied on these four modes in order to produce four new signal components. The detection of components attributed to artifacts was based on signal variance, amplitude and frequency content. Finally, the four IMFs were reconstructed for each signal using the remaining components and were subsequently summed to produce the denoised EEG signal. Signals were then segmented into epochs based on event markers and baseline-adjusted relative to a 1-s pre-stimulus baseline.

2.4 Estimation of Synchronization Waveforms

In order to evaluate the participants' cognitive status and processing load during the tasks, we studied the occurrence of event-related synchronization/desynchronization (ERS/ERD) within the electrophysiological activity [36], representing collective increases/decreases in neuronal activity at a given frequency. The main characteristic of these manifestations is that they represent induced activity, meaning they are time-locked but not phase-locked to the stimulus [37]. This method was implemented due to its applicability on our single-channel data as opposed to techniques such as event-related potentials (ERPs), though it should be noted that it requires larger time windows for stimuli presentation and interstimulus intervals – combined with a lower number of EEG epochs – compared to ERP analysis [24, 38].

Our analysis of the induced EEG activity was independently conducted for the five EEG bands (δ: 0.5–4 Hz, θ: 4–8 Hz, α: 8–13 Hz, β: 14–26 Hz, γ: 30–40 Hz), aiming to interpret results based on the known traits of each frequency band. As such, we defined the frequency bands and then calculated the induced band power (IBP) for each reconstructed signal x_f using the inter-trial covariance method on each individual sample j over all trials (i = 1, …, n) as follows:

$$IBP(j) = \frac{1}{n-1}\sum\nolimits_{i=1}^{N}\left[x_f(i,j) - \bar{x}_f(j)\right]^2 \quad (1)$$

The $\overline{x}_f(j)$ signal corresponds to the mean filtered signal of a specific band across all trials, representing evoked activity. Consequently, removing this signal gives prominence to the non-phase-locked (i.e. induced) activity that does not include evoked potentials.

The occurrence of synchronization or desynchronization within the EEG signal is identified by calculating for each sample j the percentage change P(j) of the IBP(j) relative to the mean IBP of the reference interval $[r_0, r_0 + k]$ recorded for each task.

$$IBP_r = \frac{1}{k}\sum_{j=r_0}^{r_0+k} IBP(j) \tag{2}$$

$$P(j) = (IBP(j) - IBP_r)/IBP_r \tag{3}$$

Evidently, positive values correspond to synchronization phenomena (ERS), with negative values reflecting occurrence of desynchronization (ERD). Finally, to address the lack of IBP waveforms smoothness for the extraction of statistical metrics, we applied a moving average filter with a window of 103 samples, corresponding to a recording duration of 0.2 s.

Figure 2 summarizes the processing flow applied on the EEG data, including pre-processing, induced activity waveform extraction and statistical analysis:

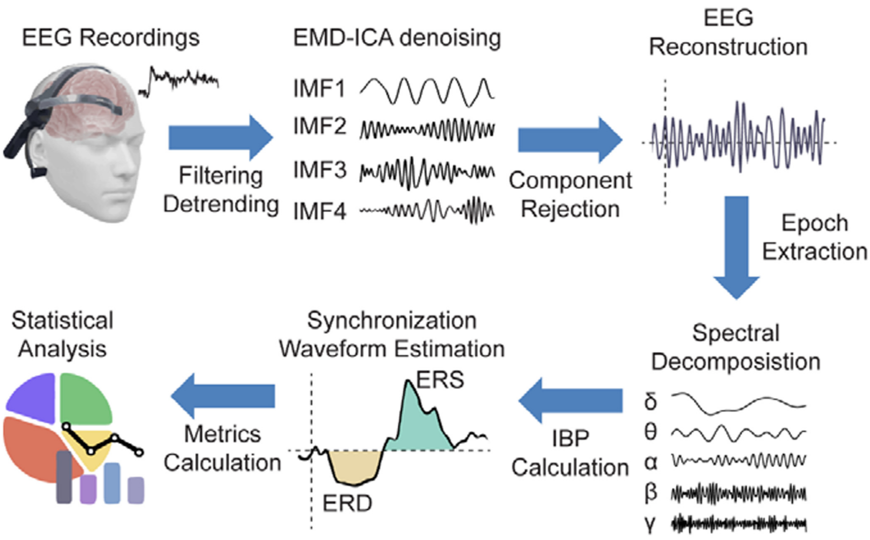

Fig. 2. Data Processing Workflow. Filtering and detrending were followed by the denoising process, where we firstly decomposed the single-channel data and then applied ICA to the resulting IMFs in order to identify and reject noisy components. The initial data channel was then reconstructed, followed by spectral decomposition and estimation of waveforms reflecting induced activity. Based on these waveforms, we extracted statistical measures for every task and each EEG band.

2.5 Statistical Analysis

Following the eventual waveform extraction, for each EEG band and each phase of every cognitive task, we extracted statistical measures of location and variability, consisting of maximum/minimum activity, mean activity, standard deviation, range and coefficient of variation (CV). With the term "activity" we denote the percentage change in the induced band power, reflecting ERS/ERD phenomena. Metrics were extracted for pre-training and post-training data. In addition, we computed behavioral measures describing the participants' performance during the cognitive tasks by calculating quantities describing sensitivity, specificity, accuracy, precision, recall rate and response time for all tasks, namely face recognition, name recall, word recall rate and recognition, as well as N-back recognition.

On comparing pre-training and post-training performances of the training and control groups and taking into account our small groups (3 participants per group), we used a t-test on each group in order to investigate the existence of features that presented a statistically significant difference between the two evaluation stages. T-tests were implemented on each feature data individually, while inference was conducted at a significance level of 5%.

3 Results

All members of the training group but one reached the set of maximum lag interval values committing less than two errors per session, with one participant failing to progress during one session. As regards the behavioral and EEG outcomes, the control group presented a statistically significant difference between the two evaluation stages only for FNM-IR recognition specificity ($p = 0.0423$), while no further differences were observed in EEG or behavioral metrics. On the other hand, the training group displayed significant differences for a total of thirteen features, presented in Table 1:

Table 1. Statistically significant features for the training group (t-test)

Feature type	Task	Task phase	Feature name	Band	Change	p-value
EEG	FNM	IR	Coefficient of variation	α	D	0.0328
			Coefficient of variation	θ	D	0.0363
		DR	Max activity	β	D	0.0241
			Coefficient of variation	δ	D	0.0009
			Max activity	θ	I	0.0399
			Standard deviation	θ	I	0.0458

(*continued*)

Table 1. (*continued*)

Feature type	Task	Task phase	Feature name	Band	Change	p-value
Behavioral	FNM	IR	Recognition sensitivity		D	0.0153
			Recognition specificity		D	0.0335
			Recognition accuracy		D	0.0206
			Name recall specificity		D	0.0075
	N-back	2-back	Sensitivity		I	0.0257
		3-back	Precision		I	0.0463
		4-back	Accuracy		I	0.0390

*IR: immediate recognition, DR: delayed recognition, I: Increase, D: Decrease

4 Discussion and Future Research

In this study, we developed an experimental protocol aiming to evaluate specific aspects of cognitive skills and investigate the influence of cognitive training in performance by introducing single-channel EEG data acquired via a mobile user-friendly device. Our minimal setup limits pre-processing alternatives, thus we resorted to a specialized single-channel denoising method combined with conventional filtering. Likewise, since extraction of reliable ERPs from cerebral areas of interest (i.e. face recognition) was not possible, we analyzed band synchronization activity that has also been implemented on previous works [39, 40]. This framework aimed to investigate inference capacity within a simplified EEG setup.

At first glance, the EEG contribution to the study of the participants' cognitive performance is evident, since we identified multiple features presenting a statistically significant change, thus confirming our initial assumption that the incorporation of single-channel measures can assist in the interpretation and validation of behavioral results. Moreover, statistical outcomes revealed almost no changes for the control group concerning performance between pre-training and post-training stages, while the training group showed differences on both EEG and behavioral metrics for a variety of features, implying that our cognitive training program had a tangible effect on the participants. Inspecting the related outcomes, we initially comment on the behavioral outcomes and on a second level we attempt to interpret these results by introducing the EEG findings.

As such, Table 1 shows an unexpected overall performance decrease of the training group for the face-name memory test. In an attempt to explain this result, we considered the participants' shared reports on occurrence of mental fatigue after the 3rd training day, as well as their reported bias during the recognition tasks. In particular, having undertaken the 4-day training program trying to avoid false recognition of familiar faces, all participants admitted a lack of confidence during the post-training evaluation, where their performance anxiety often led them into altering their intended responses, resulting to more errors compared to the pre-training evaluation. Taking into the EEG changes into account, we observed that the performance decrease was accompanied by a decrease in the coefficient of variation in the α and θ bands. Mathematically, this corresponds to a decrease in the ratio of standard deviation to the mean value for the induced band power percentage waveform. Interestingly, this may reflect improved processing [41], despite the fact that response bias and fatigue led to a reduced performance. Increases in the θ band (ERS) during the delayed recognition task also reflect a high memory load [42], with the comparison to the pre-training results supporting the participants' self-reports on fatigue occurrence.

Regarding the reduction in the β band maximum activity (ERD), this could simply refer to verbal responses of the participants during recognition [43]. However, since this was not observed during pre-training, it seems more likely that β ERD is related to enhanced cognitive control during long-term memory retrieval [44] (since it was observed during the delayed recognition task) or increased working memory information maintenance [45]. Furthermore, the coefficient of variation decrement in the δ band is also consistent with previous studies, reflecting concentration during task performance [46, 47]. Finally, no indication was provided on whether the improvements in N-back performance should be attributed to transfer effects or mere task experience.

On another note, we must highlight the observed distinction between controlled and automatic processing which was evident on the participants during the training program. Namely, when presented with a repetition face with a lag of over 10, it was clear that the participants recognized the image before promptly recalling the learning context and thus providing a negative response. The former event represented the familiarity effect, followed by the recollection effect where the participants recalled that the specific face was not part of the study list. From the authors' point of view, this observation supports the dual process theory and encourages further investigation of its underlying mechanisms as well of the repetition-lag procedure effects in a future study using electroencephalography to distinguish and compare brain activity during familiarity and recollection processes. On that premise, despite the fact that clear changes were ascertained, fatigue reported by the participants and reflected on the results prevented us from validating the beneficial effect of training, thus we intent to use a modified routine in a future study, distributing training sessions along a wider time period and adding days of rest for the participants. Furthermore, we intend to conduct a deeper analysis regarding the contribution of electroencephalography on reliable cognitive evaluation by recruiting a large number of participants in order to increase statistical power, as well as by utilizing a modified and more targeted experimental design that will allow for the recording of a higher number of EEG epochs in order to extract smoother and more representative activity waveforms, without overextending the experiment duration. In this regard, we also intend to explore the usage of a multi-channel portable EEG headset in order to employ brain connectivity metrics and extract ERPs related to face recognition. The comparison of single-channel vs. multi-channel results is expected to provide evidence with respect to the true applicability extent of single-channel measurements. The potential outcomes could bear considerable value in further comprehending the dual process theory, applying this knowledge on the study of cognitive disorders and the development of non-pharmacological interventions based on objective measures of physiological activity.

5 Conclusion

Summarizing the conducted work, we employed a wireless portable EEG device to assess the outcomes of cognitive training on memory processes. Our framework was able to ascertain the benefits of EEG regarding the evaluation of these complicated functions even in light portable setups, as well as to achieve the manifestation of statistically significant outcomes that could be attributed to training. In particular, we managed to identify changes for a variety of EEG features without the need for a multi-channel recording station that can only be applied on laboratory settings. In addition, we were able to jointly explain EEG and behavioral results, confirming the efficiency of our experimental protocol. Ultimately, the participants that followed the proposed training routine presented multiple differentiations regarding both behavioral and EEG metrics, while the control group showed almost no changes but in one behavioral feature. No EEG differences where observed for the members of the control group, as opposed to the training group that displayed activity alterations. Building on these outcomes, we intend to extend our study utilizing a refined experimental protocol employing advanced EEG analytics for gaining comprehensive insight into the cognitive mechanisms of human memory and the dual process theory.

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