Measuring Working Memory in Aphasic Individuals with Electroencephalography and N-Back Tasks

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Aphasia is a neurological condition that manifests itself through deficiencies in linguistic functions, which are essential for social interaction and activities of daily living. This deficiency is associated with a loss of working memory capacity, which is responsible for the temporary storage of information. This work sought to develop an approach to aid professionals involved in aphasia treatment and rehabilitation programs, aiming to improve the manner in which evidences of rehabilitation are obtained. The methodology is based on an electroencephalography device, which captures brain signals from individuals while they execute a task that stimulates verbal working memory. The signals are processed using an approach based on event-related potentials, which are then used as input to a statistical model trained with a scientifically validated measurement of working memory capacity. The results indicated that the error of the model was slightly larger than expected, but diminished proportionally to the amount of training samples. We conclude the study suggesting research paths to reduce the error of the model and investigate the feasibility of this approach in a clinical context.

Introduction: Aphasia is a disorder that mainly affects the elderly population, being a common sequelae of cerebrovascular accidents (CVAs) [1]. The disorder causes a significant loss of communication capacity in the individual, which can affect both language production (speaking and writing) and understanding (reading and listening), and in some cases it can even affect both. The aphasia rehabilitation process is long and uncertain, due to the variety of manifestations of the disorder and the complexity of the cognitive mechanisms involved in human communication [2]. According to studies, the deficits caused by aphasia arise from lesions in the left hemisphere of the brain, especially in Broca's and Wernicke's areas, which are involved in language production and comprehension capabilities, respectively [1].

Aiming to find the origin of the loss of communication ability, going beyond identifying the brain regions involved, several studies have identified working memory as a key aspect [3–5]. Working memory is responsible for storing a set of items for a short period of time, allowing them to be organized and processed as needed [6]. In the case of language, such items are the constituent elements of a sentence; therefore, a healthy working memory is essential to be able to form and understand intelligible sentences, with meaning [7].

Therefore, it can be understood that the degree of severity of aphasia can be inferred through working memory capacity; or, even, that working memory capacity is an indicator of the progress of the rehabilitation process. There are also traditional instruments for measuring aphasia, which consist of tests batteries where the individual must perform tasks that demand cognitive-linguistic effort, producing a score at its end. Among these tests, we can mention, for example, WAB [8] and the BIAS test [9].

Measuring aphasia is an important aspect of studies that investigate rehabilitation strategies. These studies typically carry out the application of a test to measure the severity of the disorder, followed by an intervention (such as speech therapy [2]), concluding with a new application of the test. Then, a comparison is made between the results before and after the intervention, checking whether there has been an improvement in the patient's condition.

Traditional instruments, however, have some unsatisfactory characteristics, being extensive, tiring and, mainly, asynchronous: the test result can only be viewed after completing all items and after a subsequent analysis of the answers. If there is a manner to directly monitor the progress of rehabilitation, it would be possible to overcome these negative aspects, also allowing the practitioner to continually make adjustments to their methodology, according to their observations. This is the research problem explored in this study, which we sought to solve using an approach based on a brain-computer interface.

Related works: The present study addresses the intersection between aphasia, working memory and electroencephalography. It can be seen that, in the scientific literature, there is frequent use of two of these pillars, but very rarely all three. There are studies that investigate the relationship between aphasia and working memory [5], others that use electroencephalography to analyze aphasia [10, 11] or to treat it [12], while others still use electroencephalography as a means of studying working memory [11, 13–17].

In this study, an hypothesis has been constructed that working memory capacity is an accurate biomarker of the degree of severity of aphasia, and that working memory capacity can be estimated using electroencephalography. Thus, we sought to identify, in the scientific literature, works that provided evidence that both parts of the hypothesis raised are true.

We identified some studies that used all three pillars together to obtain relevant results. Among these studies is the work of Gorisek [18], which analyzed the impact of Broca's aphasia on neuronal networks related to working memory. The authors selected ten individuals with Broca's aphasia, and a control group, also with ten individuals, without a history of aphasia. Participants performed the Sternberg task, which requires verbal working memory effort, and had their brain activity monitored using an electroencephalographic device. Through spectral density analyses, discrepancies in the *theta* and *gamma* bands were verified between groups of individuals, indicating that it is viable to use electroencephalography to identify the severity of aphasia.

Another study that investigated the relationship between aphasia, electroencephalography and working memory is that of Spironelli, Manfredi and Angrilli [11]. In this study, the authors compared a group of individuals with no history of aphasia with a group of recovered aphasics. The authors applied a working memory stimulation task called digit span, investigating the activity of both cerebral hemispheres through spectral density analysis. It was found that, in individuals without a history of aphasia, the left hemisphere had greater activity when performing linguistic tasks; however, in recovered aphasics, the authors found that the right hemisphere had more intense activation. The same behavior was not observed in visuospatial tasks, with minimal difference between the groups in this type of task. This indicates that the aphasia recovery process involves recruitment of healthy regions of the brain and that, as a result, it is necessary to consider both hemispheres when analyzing individuals with aphasia.

A third study that takes into account the same three pillars investigated in this article is that of Chang et al. [19]. In this case, working memory is not considered directly, but rather, reading comprehension of sentences, an aspect closely linked to working memory. The study considered four groups of individuals, classified according to the presence of aphasia and ability to comprehend. The participants' brain activity was measured while they performed the comprehension task and, through an analysis based on ERPs [20], it was found that the N400 component showed differences in the group of aphasic individuals with low verbal comprehension. Therefore, this component can be considered as a biomarker of the working memory capacity of aphasic individuals.

In addition to these specific studies, presented with the aim of demonstrating the relevance and feasibility of this work, a broad review of the literature was also carried out, seeking to identify statistics on the use of the following methodological aspects: approach to analyze electroencephalographic signals and working memory stimulation task. A search was carried out in the scientific paper databases PubMed, Taylor & Francis and ScienceDirect, with the following search protocol: *(electroencephalography OR electroencephalogram OR eeg) AND "working memory" AND (measure OR measurement OR measuring) AND (integrity OR capacity)*.

The search resulted in 318 articles, which were initially analyzed regarding their titles and abstracts, aiming to identify the absence of mention of measuring working memory capacity through electroencephalography and, if there was none, the article was discarded. Repeated articles, literature reviews, short articles, case studies and articles in languages other than English were also discarded. After applying this filtering procedure, 140 articles remained, which were analyzed individually, focusing on identifying the methodological aspects mentioned.

Regarding the analysis of electroencephalographic signals, it was found that the predominant approaches were: power spectral density analysis (PSD), event-related potentials (ERP) and event-related synchronization/desynchronization (ERS/ERD). Table 1 presents the frequencies of use of each approach.

Table 1. Scientific papers according to signal analysis approach.

Approach	Frequency
PSD	18 (37,5%)
ERP	**20 (41,7%)**
ERS/ERD	6 (12,5%)
Others	4 (8,3%)

It can be seen that ERP analysis is the most used approach, followed closely by PSD. Regarding the working memory stimulation task, we observed that the main tasks used were: n-back, Sternberg, DMTS and span-type tasks. Table 2 presents statistics related to this analysis.

Table 2. Scientific papers according to the working memory task.

Task type	Frequency
n-back	**26 (54,2%)**
Sternberg	8 (16,7%)
DMTS	4 (8,3%)
Span	4 (8,3%)
Others	6 (12,5%)

It is possible to verify that, with regards to the verbal working memory stimulation task, the n-back task is the most frequently used, by a considerable margin. These results contributed to the definition of the methodologies used in the present work.

Materials and Methods: In this section, we discuss the methodology adopted to address the issue raised in the Introduction, that is, a way to improve the rehabilitation process for aphasic patients, aiming to identify evidence of improvement in the patient's condition. In the present study, the biomarker adopted for the degree of severity of aphasia was working memory capacity, the measurement method of which will be described throughout this section.

Considering the problem of asynchrony in traditional aphasia tests, and the same characteristic shown in working memory tests, we decided to perform the analysis using electroencephalographic data, which can be collected in real time; additionally, being physiological data the approach is less subject to bias at the time of collection. The device selected to collect electroencephalographic signals was the OpenBCI Cyton board, which has 8 input channels. This choice was made taking into account the low cost of the device and its ease of use by beginners and enthusiasts in the field of neuroscience. A 3D helmet printed in PLA was used to support the board and electrodes, which were positioned in the following locations: Fp1, Fp2, F3, F4, F7, F8, C3 and C4.

Electroencephalographic signals were collected from individuals from two groups, with and without aphasia, while they performed a verbal working memory stimulation task. The task selected for this purpose was the n-back task, a decision made based on the frequency of use of the task in scientific literature, as can be seen in Table 2, the simplicity of the task, its automatable nature and the its flexibility [21]. The task was implemented computationally with parameters based on a set of articles that follow a similar methodology [13, 22–24], with the stimuli defined as nameable figures, presented together with their label. Although the stimulus is presented visually, as it is nameable, its encoding takes place verbally – that is, the individual stores the name of the stimulus presented in their working memory.

The application of the task was organized into five blocks, the first being for practice, as in the work of Christensen and Wright [22]. Both the 1-back and 2-back variations of the task were used. The configuration in 1-back mode was as follows, for each block (stimuli/targets): 10/2, 26/8, 24/8, 24/9 and 24/8. For the 2-back mode, we used: 10/2, 26/8, 24/8, 26/8 and 24/8.

For each block, the task was performed as follows: the stimulus is presented on the screen for 750 ms and then disappears; then, the individual has 2750 ms to inform whether the image is a target stimulus, that is, whether it is the same as the one that was presented n steps before. This input is performed by pressing the space bar. At the end of this period, an indicator is displayed for 500 ms informing whether the user got it right or wrong, according to the following definition: if the image is a target stimulus and the user pressed the space bar, it is considered a hit, or, if the user has not pressed, an error; if the image is not a target stimulus, it is considered a hit if the user did not press the space bar, and an error if they did.

With the electroencephalographic data collected from individuals, we sought to build a statistical model capable of inferring the individual's working memory capacity based on signal characteristics. To train this model, it was necessary to apply a working memory test recognized and validated by the scientific literature, to be used as a ground truth. We decided to use a subset of the tests available in the Neupsilin instrument (Brief Neuropsychological Assessment Instrument), developed by Fonseca, Salles and Parente [25]. This instrument has a low cost per application, and includes tasks validated in the literature, such as complex span [4, 21]. Three subtests were used: digit ordering (ORD), auditory span (SPAN) and immediate verbal recall (REC). Each individual's working memory capacity, symbolized by W, was obtained through a weighted average of the scores of these three subtests.

To extract numerical features from electroencephalographic data, capable of being used in the statistical inference model, the Event Related Potentials (ERPs) technique was used. This decision was made based on some observations: it is a computationally simple technique, as it is based on average operations [20]; is widely used in scientific literature, as seen in Table 1; it is favorable to be used in conjunction with the n-back task, as both are event-based. Furthermore, it can be seen that, in the literature, there are works closely related to the present one that also use this technique [13, 26, 27].

The transformation of electroencephalographic data into features through ERPs took place as follows. The signal, after being filtered with a 60 Hz notch filter and a bandpass filter between 1 and 50 Hz, was divided into windows, extracted according to the timestamp of the target stimulus presentation events of the n-back task, starting 300 ms before the event and ending 700 ms after the event. The windows were grouped into sets of 8, 16, 32 and 64 components, and the average signal for each group was computed, thus carrying out the time-locking [20] process. Then, three features were extracted from each signal: mean, maximum and latency. The extraction thresholds for these features was defined according to the following configuration, in the format *component (upper, lower)*: P100 (25, 175); N100 (75, 225); P200 (150, 350); N200 (200, 400); P300 (250, 500). The values are in milliseconds, based in the instant of the occurrence of the event. For components with prefix N, the sign was inverted to obtain the maximum value feature.

Regarding the statistical inference model, we chose to use a regression analysis based on the Support Vector Machines (SVM) technique, a robust and widely used class of algorithms [28]. Two variations of the model were used, one linear, using the least squares method, and another non-linear, using a radial basis function as the kernel. The goal of this analysis is to infer a function $f(X) = W$, where X represents the set of features extracted through ERP analysis and W represents the individual's working memory capacity. To train the model, the k-fold cross-validation technique was used, with $k = 5$ [29], and the metric used to evaluate the models was the root mean squared error. In the next section, the results obtained are presented.

Results: In total, 14 individuals participated in the study described in this work, 7 with aphasia and the other 7 without. The Neupsilin test was applied to all individuals, and no discomfort, irritation or refusal was observed. The application was carried out by a psychology student as the first stage of the experiment. Using the results obtained from these exams, the W value was calculated as follows: the values of the three subtests were normalized according to the maximum score of each subtest, and then a logistic regression analysis was carried out, with the independent variables being the subtest scores and the dependent variable whether the individual has or doesn't have aphasia. After the logistic regression analysis, which achieved an accuracy of 78.57%, a weighted average of the three subtests was performed according to the coefficients obtained by the model, being 0.7494 for ORD, 0.8884 for the SPAN and 1.1117 for REC. The normalized scores, as well as the W values, can be viewed in Table 3.

Table 3. Participants of the study, subtest scores and value of W.

ID	Aphasia	Age	ORD	SPAN	REC	W
A1	Yes	59	0.200	0.214	0.222	0.5873
A2	Yes	61	0.300	0.179	0.000	0.3835
A3	Yes	61	0.300	0.321	0.000	0.2856
A4	Yes	64	0.200	0.500	0.111	0.7176
A5	Yes	81	0.000	0.429	0.000	0.3808
A6	Yes	64	0.200	0.643	0.000	0.7210
A7	Yes	80	0.200	0.857	0.000	0.9114
C1	No	61	0.200	0.643	0.444	1.2151
C2	No	67	0.400	0.571	0.444	1.3016
C3	No	68	0.700	0.714	0.666	1.9004
C4	No	85	0.700	1.000	1.000	2.5248
C5	No	81	0.800	1.000	0.333	1.8586
C6	No	71	0.200	1.000	0.444	1.5324
C7	No	77	0.500	1.000	0.333	1.6337

Then, a set of experiments was carried out to investigate the relevance of each independent variable, using linear correlation analyses and visual inspection of scatter plots. It was found that, in all components, the correlation between latency and W is very close to zero, therefore we chose to discard this feature, concluding that the working memory capacity does not impact the latency of occurrence of the ERP components. It was also possible to verify that the average and maximum features have a similar behavior and, therefore, to limit the number of independent variables, we decided to use only the average, an approach also recommended by Luck [20]. Then, statistical inference models were constructed, in linear and non-linear modes, for the 4 types of grouping described in Section 3. Training was carried out per channel, in order to achieve more specific inferences, and the results are presented in Table 4. Both models were implemented in Python, using the Scikit-learn library [30].

Table 4. RMSE values for the analysis by channel.

	Linear				SVM			
Ch	G8	G16	G32	G64	G8	G16	G32	G64
1	0.816	0.839	1.061	1.590	0.880	0.828	0.968	0.945
2	0.832	0.902	0.954	0.927	0.873	0.918	0.915	0.807
3	0.893	1.048	1.182	1.021	1.007	0.999	1.028	0.907
4	0.782	0.919	0.842	0.983	0.752	0.798	0.654	0.769
5	0.752	0.777	0.930	0.652	0.735	0.810	0.866	0.923
6	0.776	0.909	1.226	1.375	0.789	0.761	0.841	0.868
7	0.825	0.958	1.033	1.121	0.652	0.696	0.628	0.884
8	0.863	0.859	0.858	1.463	0.969	0.916	0.905	1.021
Avg.	0.817	0.901	1.011	1.141	0.832	0.841	0.851	0.890

Using t tests, we found that, in sets with groupings of 8 and 16, there is no significant difference between the models; in the groups of 32 and 64, however, p-values of 0.04 and 0.06, respectively, were observed. Analyzing the averages, shown in the last line of Table 4, it is possible to conclude that, analyzing each channel individually, the approach based on SVMs is superior, as it presents a lower RMSE.

Continuing, a combined analysis of all channels was carried out, expanding the number of samples available for training the model. For this approach, only one model of each type was trained for each dataset, without grouping the data by the channel the sample came from. Other aspects of the procedure remain unchanged. The results of this analysis are presented in Table 5.

Table 5. RMSE values considering all channels combined.

Group size	RMSE - Linear Regression	RMSE - SVM
8	0.7834	0.8605
16	0.7956	0.9144
32	0.7740	0.9204
64	0.8049	0.9840

It can be seen that, in this case, the linear model presented a lower error than the SVM. It can be understood, also observing the differences between the group sizes, that the quality of the linear model increases proportionally to the number of samples available, eventually surpassing the SVM, which also benefits from the increase in samples, but on a smaller scale.

Conclusions: In this study, a computational approach was developed to measure working memory capacity, using non-invasive electroencephalography, aiming to contribute to the rehabilitation process of aphasic individuals. Such individuals find themselves in an impaired condition, being subject to a low quality of life due to difficulties related to language, which is one of the main means of building and maintaining relationships between individuals.

To address this problem, we sought to develop a methodology for inferring working memory capacity through the analysis of electroencephalographic signals, using a statistical model trained with data from the Neupsilin exam. Two groups of individuals participated in the study, one with aphasia and the other without, with each individual undergoing a working memory stimulation task while their brain activity was collected, which was analyzed using an ERP-based approach.

We consider that the objective of the study was achieved, with an experimental procedure being carried out that allowed the construction of a statistical model trained with the Neupsilin test, using the individuals' electroencephalographic signals as input. However, we found that the resulting RMSE remained above the standard deviation of the values of W of the group of individuals without aphasia (0.40905), which can be considered as representative of the common variability in working memory capacity among individuals without neurological conditions. We consider that the main reason for this result is the limited number of training samples, as it is known that to generate good quality ERP waves it is necessary to use a large number of events, sometimes around 100, as commented by Luck [20]; however, increasing the number of events, the size of the training set decreases, and it was found that the models benefit considerably from a large number of training samples. Therefore, we conclude that expanding the study, in order to obtain more training data, is one of the main directions for future work.

We also recommend th following points as suggestions for continuing this research: to implement an on-line analysis approach, together with a graphical interface, to enable the use of the solution by professionals in a clinical setting; to use another device to capture electroencephalographic signals, as it is known that the Cyton board is susceptible to noise, and with more robust devices the inference model may be capable of making predictions with lower error rates; and to carry out analyses of emotional valence based on the electroencephalographic signals obtained, seeking to determine whether the data collection procedure is being hampered by negative emotional reactions, and seeking ways to improve this procedure if that is the case.

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References

1. Damasio, A.R.: Aphasia. New England Journal of Medicine 326(8) (1992). doi:10.1056/NEJM199202203260806. http://www.nejm.org/doi/abs/10.1056/NEJM198307283090407http://www.nejm.org/doi/abs/10.1056/NEJM199202203260806
2. Doogan, C., et al.: Aphasia Recovery: When, How and Who to Treat? Current Neurology and Neuroscience Reports 18(12), 90 (2018). doi:10.1007/s11910-018-0891-x. http://www.embase.com/search/results?subaction=viewrecord{&}from=export{&}id=L624440215{%}0Ahttp://dx.doi.org/10.1007/s11910-018-0891-xhttp://link.springer.com/10.1007/s11910-018-0891-x
3. Hula, W., McNeil, M.: Models of Attention and Dual-Task Performance as Explanatory Constructs in Aphasia. Seminars in Speech and Language 29(03), 169–187 (2008). doi:10.1055/s-0028-1082882. http://www.thieme-connect.de/DOI/DOI?10.1055/s-0028-1082882
4. Wright, H.H., Fergadiotis, G.: Conceptualising and measuring working memory and its relationship to aphasia. Aphasiology 26(3-4), 258–278 (2012). doi:10.1080/02687038.2011.604304. http://www.tandfonline.com/doi/abs/10.1080/02687038.2011.604304
5. Christensen, S.C., Wright, H.H., Ratiu, I.: Working memory in aphasia: Peeling the onion. Journal of Neurolinguistics 48, 117–132 (2018). doi:10.1016/j.jneuroling.2018.02.001. https://linkinghub.elsevier.com/retrieve/pii/S091160441730115X
6. Baddeley, A.D., Hitch, G.. Working memory. In: Psychology of Learning and Motivation - Advances in Research and Theory. vol. 8, pp. 47–89. Academic Press (1974). https://linkinghub.elsevier.com/retrieve/pii/S0079742108604521
7. Veraksa, et al.: The Relationship between Executive Functions and Language Production in 5–6-Year-Old Children: Insights from Working Memory and Storytelling. Behavioral Sciences 10, 52 (2020). doi:10.3390/bs10020052
8. Shewan, C.M., Kertesz, A.: Reliability and Validity Characteristics of the Western Aphasia Battery (WAB). Journal of Speech and Hearing Disorders 45(3), 308–324 (1980). doi:10.1044/jshd.4503.308. http://pubs.asha.org/doi/10.1044/jshd.4503.308
9. Kleih, S.C., et al.: Toward a P300 Based Brain-Computer Interface for Aphasia Rehabilitation after Stroke: Presentation of Theoretical Considerations and a Pilot Feasibility Study. Frontiers in Human Neuroscience 10(NOV2016), 1–13 (2016). doi:10.3389/fnhum.2016.00547. http://journal.frontiersin.org/article/10.3389/fnhum.2016.00547/full
10. Honda, H., et al.: Diagnosis of Aphasia from Electroencephalogram Using Neural Network. IFAC Proceedings Volumes 31(8), 467–472 (1998). doi:10.1016/S1474-6670(17)40230-8. http://dx.doi.org/10.1016/S1474-6670(17)40230-8https://linkinghub.elsevier.com/retrieve/pii/S1474667017402308
11. Spironelli, C., Manfredi, M., Angrilli, A.: Beta EEG band: A measure of functional brain damage and language reorganization in aphasic patients after recovery. Cortex 49(10), 2650–2660 (2013). doi:10.1016/j.cortex.2013.05.003. http://dx.doi.org/10.1016/j.cortex.2013.05.003
12. Dominguez, A., et al.: Transcranial direct current stimulation improves word production in conduction aphasia: Electroencephalographic and behavioral evidences. International Journal of Clinical and Health Psychology 14(3), 240–245 (2014). doi:10.1016/j.ijchp.2014.02.001. http://dx.doi.org/10.1016/j.ijchp.2014.02.001
13. Dong, S., et al.: Individual differences in working memory capacity are reflected in different ERP and EEG patterns to task difficulty. Brain Research 1616, 146–156 (2015). doi:https://doi.org/10.1016/j.brainres.2015.05.003. https://www.sciencedirect.com/science/article/pii/S0006899315003881
14. Rodriguez-Martinez, E.I., et al.: Spontaneous theta rhythm and working memory co-variation during child development. Neuroscience Letters 550, 134–138 (2013). doi:https://doi.org/10.1016/j.neulet.2013.06.054. https://www.sciencedirect.com/science/article/pii/S0304394013006010
15. Borhani, S., et al.: Gauging Working Memory Capacity From Differential Resting Brain Oscillations in Older Individuals With A Wearable Device. Frontiers in Aging Neuroscience 13(February) (2021). doi:10.3389/fnagi.2021.625006
16. Shi, Z., Gao, X., Zhou, R.: Frontal theta activity during working memory in test anxiety. NeuroReport 26(4), 228–232 (2015). doi:10.1097/WNR.0000000000000334
17. Jaušovec, N., Jaušovec, K.: Increasing working memory capacity with theta transcranial alternating current stimulation (tACS). Biological Psychology 96, 42–47 (2014). doi:https://doi.org/10.1016/j.biopsycho.2013.11.006. https://www.sciencedirect.com/science/article/pii/S030105111300238X
18. Rutar Gorišek, V., et al.: Beyond aphasia: Altered EEG connectivity in Broca's patients during working memory task. Brain and Language 163, 10–21 (2016). doi:https://doi.org/10.1016/j.bandl.2016.08.003. https://www.sciencedirect.com/science/article/pii/S0093934X16301766
19. Chang, C.T., et al.: Predictability effect on N400 reflects the severity of reading comprehension deficits in aphasia. Neuropsychologia 81, 117–128 (2016). doi:10.1016/j.neuropsychologia.2015.12.002
20. Luck, S.J.: An Introduction to the Event-Related Potential Technique. A Bradford Book. Bradford Books (2014). https://books.google.com.br/books?id=SzavAwAAQBAJ
21. Mayer, J.F., Murray, L.L.: Measuring working memory deficits in aphasia. Journal of Communication Disorders 45(5), 325–339 (2012). doi:10.1016/j.jcomdis.2012.06.002. http://dx.doi.org/10.1016/j.jcomdis.2012.06.002https://linkinghub.elsevier.com/retrieve/pii/S0021992412000664
22. Christensen, S.C., Wright, H.H.: Verbal and non-verbal working memory in aphasia: What three n -back tasks reveal. Aphasiology 24(6-8), 752–762 (2010). doi:10.1080/02687030903437690. https://www.tandfonline.com/doi/full/10.1080/02687030903437690
23. Arjona-Valladares, A., et al.: Event-related potentials associated to N-back test performance in schizophrenia. Progress in Neuro-Psychopharmacology and Biological Psychiatry 111, 110347 (2021). doi:10.1016/j.pnpbp.2021.110347. https://www.sciencedirect.com/science/article/pii/S0278584621001068
24. Wright, H.H., et al.: Processing distinct linguistic information types in working memory in aphasia. Aphasiology 21(6-8), 802–813 (2007). doi:10.1080/02687030701192414. http://www.tandfonline.com/doi/abs/10.1080/02687030701192414
25. Fonseca, R.P., Salles, J.F., Parente, M.A.M.P.: NEUPSILIN: Instrumento de Avaliação Neuropsicoplógica Breve. São Paulo: Vetor (2009)
26. Daffner, K.R., et al.: Mechanisms Underlying Age- and Performance-related Differences in Working Memory. Journal of Cognitive Neuroscience 23(6), 1298–1314 (2011). doi:10.1162/jocn.2010.21540. https://direct.mit.edu/jocn/article/23/6/1298/5109/Mechanisms-Underlying-Age-and-Performance-related
27. Morrison, C., Kamal, F., Taler, V.: The influence of working memory performance on event-related potentials in young and older adults. Cognitive Neuroscience 10(3), 117–128 (2019). doi:10.1080/17588928.2019.1570104. https://doi.org/10.1080/17588928.2019.1570104https://www.tandfonline.com/doi/full/10.1080/17588928.2019.1570104
28. Smola, A.J., Schölkopf, B.: A tutorial on support vector regression. Statistics and Computing 14(3), 199–222 (2004). doi:10.1023/B:STCO.0000035301.49549.88. http://link.springer.com/10.1023/B:STCO.0000035301.49549.88
29. Fushiki, T.: Estimation of prediction error by using K-fold cross-validation. Statistics and Computing 21(2), 137–146 (2011). doi:10.1007/s11222-009-9153-8
30. Pedregosa, F., et al.: Scikit-learn: Machine Learning in Python. Journal of Machine Learning Research 12, 2825–2830 (2011)
31. Oldoni, M.L., et al.: Measuring working memory usage on aphasic individuals and analysis of emotional valence through electroencephalography. Computer Methods and Programs in Biomedicine Update 1, 100006 (2021). doi:https://doi.org/10.1016/j.cmpbup.2021.100006. https://www.sciencedirect.com/science/article/pii/S2666990021000057