University of Glasgow

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ID NUMBER: ……

DATE: …20th…August…2018….

WORD COUNT: ……8300……..

SUPERVISOR: ……Dr Kerry Kilborn……..

MSc Psychological Studies
Dissertation 2017-18
Delivered jointly:

Education (EDUC5839) and
Psychology (PSYCH5040)

Semantic memory, EEG markers & Cognitive Decline

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Semantic memory, EEG markers & Cognitive Decline

[1]MSc. Psychological Studies

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Acknowledgments

I would like to thank Dr. Kerry Kilborn, Dr. Gabriela Cruz &
Christoph Daube for their support.

Abstract

This dissertation takes a theoretical approach to addresses the existing gap between current episodic memory theory and clinical phenotypes found on memory disorders. This issue is particularly relevant to Alzheimer's disease diagnose and to the efforts on diagnosing Alzheimer's disease with electroencephalography (EEG) markers.

The dissertation uses well know computational methods and multivariate patter analysis to help start bridging the marker measures, theoretical models and the observable clinical memory disorders simultaneously.

I used secondary data from 73 healthy elderly participants that took a cross-modal old/new behavioural task while being recorded with a 128-channel EEG sensor. I will test for significant correlation between the representational similarity of the brain response and representational similarity of 110 clustered image-sound stimuli. Additionally, I carried out an event related spectrum perturbations analysis to gain information on the oscillatory nature of the semantically grouped responses.

I found a significant correlation between RSA brain response and RSA semantic memory model. In addition, the oscillatory data signals for a different response modulated by theta and alpha powers depending on the cluster presented.

Introduction

In the next few paragraphs, I will go through the biological definition of Alzheimer's and then expand upon an Alzheimer's disease-specific symptom: episodic memory disorder. Then, I will proceed to lay down the existing gap between how individuals experience memory disorders in Alzheimer's and how memory theory accounts for such realities. Finally, I will provide an overview of how this dissertation contributes to finding solutions to the problem.

Alzheimer's disease Definition

Alzheimer's disease is already among the leading causes of death in most high-income countries (Alzheimer's Association, 2017). By 2050, the Alzheimer's Association (2017) expects a new case of Alzheimer's disease (AD) to develop every 3 seconds. Therefore, the need to have an effective and available method of diagnosis becomes more evident. This will allow for an accurate understanding of AD prevalence, incidence and improvement in patients' lives (Alzheimer's Association, 2017).

Alzheimer's disease is usually defined as a *clinico-pathological* entity (Cummings, 2004) that requires (1) for the presence of a progressive dementia and (2) a specific neuropathological change (e.g., senile plaques). This definition is problematic when we try to observe senile plaques. For the time being, the only known way to gather and detect senile plaques is by looking through brain tissue under the microscope. In order to achieve this, most neuropathological investigations manage to access brain tissue only at post mortem or, in rare occasions, by a brain biopsy. In practical terms, this implies that AD can be diagnosed with 100% accuracy only after the patient's death.

A way to circumvent this problem is to identify and use biomarkers of the disease. Biomarkers are naturally occurring molecules, genes, or characteristics by which a particular pathological process or disease can be identified. For AD, the two most commonly used biomarkers are a peptide called Amyloid-β (the main component of the

senile plaques) and a protein called Tau. The use of these biomarkers (and memory tests) had led to a widely adopted classification of an early stage in AD called “probable AD” (McKhann, Drachman, Folstein, Katzman, Price & Stadlan, 1984).

These changes have sparked a debate regarding the definition of AD. New research criteria proposed and advanced by the International Work Group for Alzheimer's Diagnostic Criteria (IWG, 2010) suggest that AD should be understood as a *clinico-biological* entity, that is to say, the diagnosis of AD should be made when there are both clinical (episodic memory defects of the amnesic type) and in-vivo biological evidence (e.g., known biomarkers such as Amyloid-β or phospho-tau) of AD pathology (Cummings, Dubois, Molinuevo & Scheltens, 2013).

Alzheimer's Disease an Episodic Memory Disorder

Episodic memory is “an information processing system that (a) receives and stores information about temporally dated episodes or events, and about temporal–spatial relations among these events, (b) retains various aspects of this information, and (c) upon instructions transmits specific retained information to other systems, including those responsible for translating this information into behaviour and conscious awareness” (Tulving, 1972, p. 385). However, episodic memory is not fully accounted for in observed symptoms of AD.

The new AD research definition no longer requires the clinical presence of dementia. Instead, free recall and normalised cueing play a key role on its detection. Free recall refers to a classical psychological task in which participants are asked to remember and callout as many items as possible from a list usually pertaining to a category. Normalised with cueing refers to words or phrases that aid recall of previously experienced stimuli (Goldstein, 2014).

As recommended on the second version of the International Working Group for Alzheimer's Disease Diagnosis (IWG-2), clinical symptoms of AD exist when the episodic

memory is impaired. The recommended detector for episodic memory disorders is the "free and cued selective reminding test" (Dubois et al., 2014). That is to say, there is presence of a specific memory profile characterised by a low free recall that is not normalised by cueing (Dubois et al., 2014; Dubois & Albert, 2004) and is a valid clinical marker of typical AD.

Dementia is a set of symptoms that visibly affects an individual's ability to perform. Episodic memory disorder, on the other hand, is heterogeneous (e.g., visual memory, semantic memory, autobiographical memory, etc.) and on a moderate level does not affect an individual's ability to perform. Replacing dementia with episodic memory disorder as a requisite allows for timely diagnosis but increases uncertainty on account of the aforementioned reasons.

Having in mind the three classifications of AD (Typical, Atypical & Mixed AD), an estimated 6-14% of AD cases present variation in the typical memory symptoms. Each of these atypical forms of AD present with relative preservation of memory (Dubois et al., 2014). Mixed AD has been reported in 50% of all AD autopsies (Schneider, Wilson, Bienias, Evans, & Bennet, 2004). In IWG-2, the atypical AD manifestation includes four variants (Posterior, Logopenic, Frontal variant, and Down syndrome variants). IWG-2 shows that topographical markers as well as Tau PET (Phillips et al., 2018) can also be used to characterise the clinical phenotype.

It is not clear which are the clinical cores to each of these atypical AD presentations, whether they share the same conceptual foundation in cognitive theory, and how they can be operationalised in terms of the test selected (Dubois et. al 2014). There is a gap between specific clinical phenotypes (Posterior, Logopenic, Frontal & Down's) in AD and the current cognitive theoretical models. Another way of saying it is that we cannot be sure what is wrong with the memory of some AD patients because their

alterations do not seem to fit with current memory concepts. Also, they do not account for how they are affected by brain pathology.

Semantic Memory Models as a Broader Concept of Episodic Memory

In an effort to address the gap between atypical clinical phenotypes in AD (Posterior, Logopenic, Frontal, Down's variants) and the current cognitive models of memory, we will use and understand episodic memory as an equivalent to semantic memory.

In 1972, Tulving made explicit the difference between semantic and episodic memory. He stated that semantic memory is a memory system that does not necessarily relate to spatiotemporal events and that it can be used as input perception in addition to previous cognitive structure concepts (e.g., memory of words). In contrast, episodic memory is based exclusively on perceptual experiences of spatiotemporal events (e.g., remembering a trip to the beach).

Modern semantic models believe that semantic memory is built from repeated episodic experiences (Busemeyer, Wang, Townsend, & Eidels, 2015). I assume that these models understand that whenever someone encounters a semantic representation (e.g., word, image), it enters the memory. It starts as a perceptual memory, which is associated with the hippocampus (Aggleton & Brown, 1999); later on, if the memory is encoded, it passes on to establish neuronal connections along with other memories, thus becoming an increasingly thoughtful and abstract concept in memory, associated with the cortex (Cabeza, Ciaramelli, Olson, & Mescovich, 2008).

This implies also that our memory representation is increasingly defined by the *context* in which it is stored. Context here refers to both the circumstances in which the observer encountered the semantic representations (e.g., me now at the beach) and the other cognitive structures associated with the representations (e.g., all the childhood, adolescent, and various geographical location connection memories that enrich my concept

of the beach). Therefore, semantic and episodic memories, although conceptually different are indistinguishable when recalled (Greenberg & Verfaillie, 2010; Andrews, Vigliocco, & Vinson, 2009).

For this study, I use a distributional semantic model. This model is certainly not new, dating back to Wittgenstein (1953). The usual way to summarise it is Firth's (1957) phrase, "You will know a word by the company it keeps." Essentially this means looking into corps of text and establishing how words relate to each other.

Electroencephalogram Markers and Cognitive Decline

To bring closer the gap between atypical clinical phenotypes in AD (Posterior, Logopenic, Frontal, Down's variants) and the current cognitive models of memory, the electroencephalogram (EEG) marker could be of great use.

In recent years, studies have proposed a variety of computational approaches to detect subtle perturbations in the EEG signal of AD patients (Dauwels, Cichoki, & Vialatte, 2010). That is to say, professionals are using algorithms to process EEG signals to tell apart healthy elderly controls from mild cognitively impaired (MCI) and preclinical AD (preAD) patients with accuracies, sensitivities, and specificities that range between 70% to 90%. Recent reviews have found that AD makes ***EEG signals slower and less complex and changes their synchrony*** (Horvath, Csukly, Szucs, & Sakovics, 2018; Dauwels et al., 2010). Technicians can obtain EEG markers using different signal processing measures.

Signal processing methods change depending on the task. The original signal is transformed using the Fourier series or Wavelets series. They can be time fixed, and we can see wave amplitudes and latencies, average them together, and use them in a discrete or continuous way – transformed, filtered, etc. In our case, we have two main considerations: (1) there is an event or stimulus and (2) the oscillatory response. I chose

the oscillatory response as I think it is especially informative of how patients are recalling memory.

Contrary to what was previously understood, brain waves appear to have an important role in brain area interactions (Mankin, 2018; Zhang, Watrose, Patel, & Jacobs, 2018). Therefore, I have focused on signal processing techniques that could represent oscillations behaviour over a period of time. This focus allows me to observe the brain's electrical responses after the participant's experience cross-modal image-sound. So-called time-frequency maps are the most typically used approach to this kind of situation (e.g., Shanin, Picton, & Miller, 2009). Time-frequency measures are spectral components of a time series. These graphs depict the power of a set of frequency bands against time, so they show how much of the signal's energy comes from the frequency f at the time instance t (van Drongelen, 2018, p. 437). I will explain this in more detail in the statistical analysis section.

Representational Similarity Analysis

Representational similarity analysis (RSA) is a powerful tool that enables professionals to test how significant the relation is between semantic distribution matrices and to find out how much of this is reflected in their relation to the hold in the brain in a broad and direct fashion. We believe that if these relations exist, we will be able to more accurately diagnose atypical AD disease in the future.

RSA is a particular type of multivariate pattern analysis (MVPA) that is commonly used in functional magnetic resonance imaging (Fonteneau, Kriegeskorte, & Marslen-Wilson, 2012). Multivariate pattern analysis has been successfully used in some studies using EEG (Fonteneau et al., 2012; King & Dehaene, 2014; Chan, Halgren, Marinkovic, & Cash, 2010; Turner, Johnston, de Boer, Morawetz, & Bode, 2017). Cichy and Pantazis (2017), after a comparative study between magnetoencephalography (MEG) and EEG, suggested a wider adoption of these methods in both MEG and EEG research.

RSA tests hypothesise about the representational geometry of semantic representations and the brain's responses, which is characterised by the representational dissimilarities among the stimuli (Kriegeskorte & Kievit, 2013). To understand this better, let's consider the response time (RT) of an individual during any experimental task. This RT can be decomposed into different attributes or factors (e.g., correct/incorrect, latency, type of question, etc.). A mathematical function can collapse all of these factors into a single point – a typical example of this procedure is the single point we drew in school when using the Euclidean graphic that was determined by two factors x and y). This point we have drawn in space has a distance between itself and other points we have drawn in space. The same procedure can be applied to the brain's physiological information, therefore making it possible to compare distances between the tasks and brain data.

This Dissertation

The present study will address the gap by adopting a model-based cognitive neuroscientific approach (Love, Palmeri, & Turner, 2016; Forstmann & Wagenmakers, 2015) to test for a relation between the distribution of semantic representations in space along with the distribution of physiological responses in the brain. We will understand semantic representations as an abstract language in which meaning can be conveyed (e.g., image-sound stimuli; Vigliocco & Vinson, 2007). The idea is to corroborate or disprove the distributional semantic model.

This approach adopts a well-known theoretical model from mathematical psychology (Latent Semantic Analysis) along with a multivariate pattern analysis (Representational Similarity Analysis).

The procedure started with 110 images from a previous EEG AD marker study, distributed along a theoretical "semantic space". I then formed 12 hierarchical clusters with the images. I used electroencephalogram data (EEG) of 73 healthy elderly participants from the primary study to measure brain activity. I averaged and grouped the

EEG data, replicating the same previously grouped clusters. I then analysed the primary study data using representational similarity analysis (RSA) to see if there is a correlation between the distribution of the images and the distribution of the physiological response.

Furthermore, I used time-frequency maps to gain insight into the brain wave activity of the formed clusters, even though no significance levels were tested. All of these steps will be explained in more detail in the methods section.

I hypothesise that the characteristics of the representation of brain activity (EEG frequencies analysed through representational similarity analysis) will correlate to the characteristics of the representation of the latent semantic computational model. I also expect to extract oscillatory information from the primary study data for future research.

I hope these findings will help us to determine whether semantic distributional models have a correlate in the brain. I also hope to help bridge our understanding of the atypical clinical phenotypes in AD and cognitive memory models and to help standardise memory tests along with EEG as a diagnostic tool for AD.

Method

Sample and Participant Selection

This dissertation is an analysis based on secondary data from a previous clinical study (Tieges, Price, Hughes, McLean, Conway & Kilborn, 2010). The primary study developed a behavioural and event-related potential (ERP) marker for mild AD. The primary study gathered 76 controls and 83 AD patients who undertook a cross-modal behavioural task. The final control set of healthy elder participants was 73 (36 men), since data for three controls were rejected due to various failures in data registration. The mean age of the control group was 73.30 years (SD = 5.92). This study uses only the control group.

The information was gathered in 2010 at four clinics: Cognatec Research Centre Memory Clinic (Blackpool), Bradford Memory Clinic (Bradford), Memory Assessment Research Centre (Southampton), and Glasgow Memory Clinic (Clydebank).

Primary study's physiological recording approach

The researchers from the primary study received written consent from every participant prior to entry. At the beginning of the experiment, the participants and patients went through a brief background presentation and explanation of the procedure. Next, they were seated in front of a computer monitor with speakers placed on either side, after which they were prepared for the EEG recordings.

The researchers carried out a sound test to assess the optimal sound level of the spoken words for each participant. The words "Press New" and "Press Old" were presented in white on a black background (twelve trials in total). Participants were instructed to respond by pressing the indicated button, and auditory feedback was given through the spoken words, "correct" or "incorrect". This procedure allowed participants to familiarise themselves with the response device. The total duration of the memory test

amounted to approximately 25 minutes. The study was performed in accordance with the Declaration of Helsinki (WMA, 1974).

All EEG data obtained in the primary study were recorded on an electroencephalogram (EEG) signal from a 128-channel Geodesic Sensor Net (Electrical Geodesics Inc., Eugene, Oregon; Tucker, 1993). Impedances were kept below 50, band-pass filtered between 0.1 and 200 Hz. The ground electrode was positioned at the vertex (i.e., along the midline, anterior to Fz). The channel configuration is shown in the following 2D scalp figure. It shows the distribution of the 128 channels used and in colours the defined groups of channels. I formed groups to study based on visually detecting in the scalp the more coherent areas. Later on the analysis section, all electrodes are considered one group, later central groups (left and right), and the occipital group.

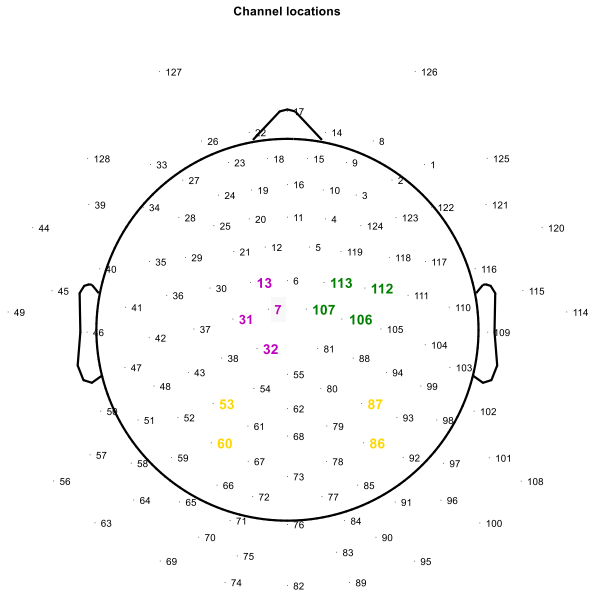


figure 1. In purple the left central electrodes, in green the right central electrodes and in yellow the occipital electrodes used later to run RSA and ERSP analysis.

Primary Data Artefact Removal

This dissertation removed the same corrupted data epochs as the primary study had removed. This artefact removal technique was applied only to the subset data used in the time-frequency analysis. The RSA analysis was carried out without artefact removal.

Muscle and eye movement artefacts were extracted from EEG data in the following steps. First, an Independent Component Analysis (ICA) was carried out using EEGLAB software (Delorme & Makeig, 2004). Next, the time course of every ICA component was correlated with each of the vertical (4 channels) and horizontal (2 channels) electrooculogram (EOG) channel time courses. The 11 ICA components that correlated highly with one or more EOG channel time courses (between 7 and 25 components) were removed from the EEG. Subsequently, epochs containing artefacts in one or more channels as well as noisy channels were detected and omitted from further analysis.

This procedure allowed participants to familiarise themselves with the response device, and volume was adjusted to a comfortable level. The memory test was preceded by a training session of three practice blocks of ten trials each, followed by the first test block. After a short break, two more practice blocks and the final test block were completed. Total duration of the memory test amounted to approximately 25 minutes. The study was performed in accordance with the Declaration of Helsinki (Revised; 2000).

Procedures

Cross-modal associative task. All of the procedures took place as part of the primary study. The cross-modal task stimulated both visual and hearing perception modes for all participants. Participants were exposed to pairs of related stimuli (a drawn image and a spoken word) presented simultaneously on a computer screen and speaker, respectively. Spoken words and image names were controlled for written length and written frequency (Francis & Kucera, 1982). The researchers substituted written norms for

spoken word norms because the latter are not extensive enough to provide a sufficient control across all words and images used in this study.

The colour images were presented in central vision on a black background, and the spoken words were presented through high quality studio monitors. A chinrest provided a constant viewing distance from the monitor of approximately 70 cm (visual angle of 2.7° x 2.0.°)

After either a short or long delay (6 or 39 intervening items, respectively), some stimulus pairs were presented for the second or third time. Participants were asked to decide whether each stimulus pair was presented for the first time (new item) or had been presented previously (old item). They gave their judgment of the new and old by pressing a button on the left or the right, respectively. A total of 270 items were presented: 110 in the New condition (i.e., items presented for the first time), 100 in the Old/Short condition (i.e., items presented a second time after 6 intervening items), and 60 in the Old/Long condition (items presented a second time after 39 intervening items).

On each trial, a stimulus pair was presented with a 3-second duration, after which the screen turned black for 1 second. Participants had to give their response within 3 seconds following stimulus onset. The items were presented in two blocks to allow for a rest period.

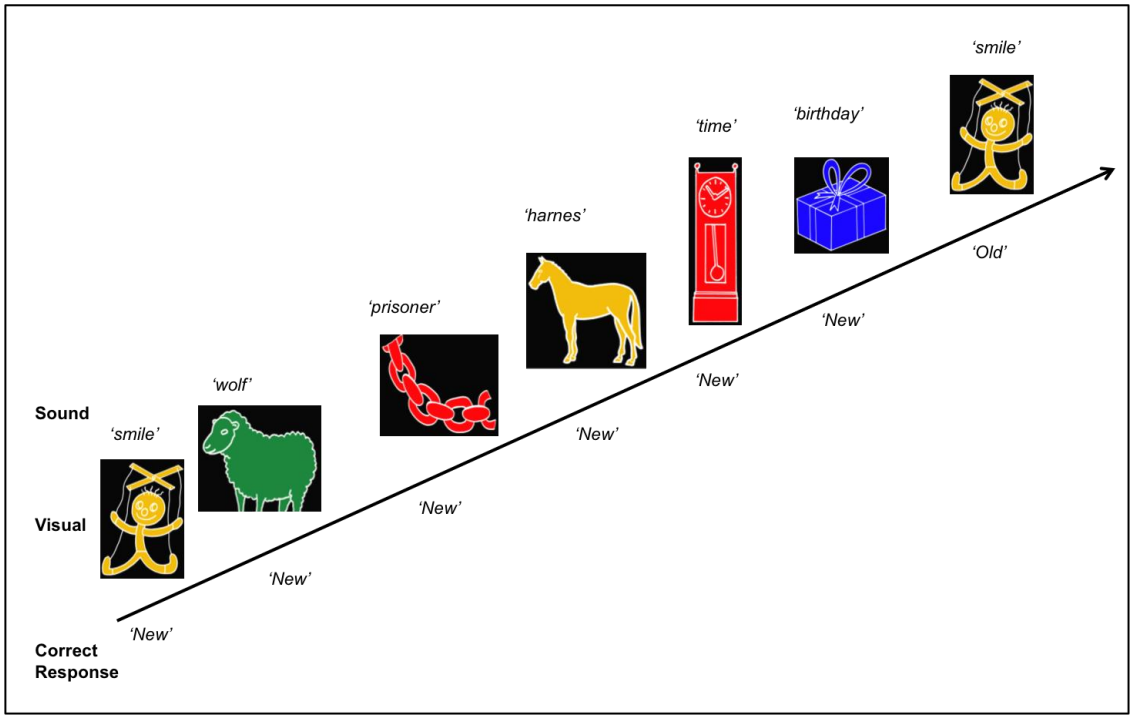


figure 2. Schematic of the continual cross-modal encoding and recognition task. During the primary study, each coloured picture was followed by a related spoken word. Some were shown only once, some were showed twice and some three times.

Data analysis. EEG data were segmented off-line into 270 single-trial epochs of 4000 ms (1000 ms pre-stimulus). The researchers in the primary study passed the data used in the time-frequency graphics through a low-pass filter at 30 Hz using NetStation software. Later on this study, they passed them through a high-pass Butterworth filter, selected for its easy implementation and its magnitude response that is maximally flat in the pass band (Gallego-Jutglà, Solé-Casals, Vialatte, Dauwels & Cichocki, 2015, p. 6).

Word comparison using latent semantic analysis. I developed 110 images and sounds from the ADEPT primary task to form a cross-modal behavioural test. I submitted these images on June 2018 as input to a latent semantic analysis comparison program (Laham & Steinhart, 2015) and received a 110 x 110 symmetric matrix that holds the cosine comparisons between images. I then sorted the images in alphabetical order and compared them to each other using a semantic space 300 factor called '1st year college'.

A semantic space is a mathematical representation of a large body of text. It functions like the two axes were we can place a point in our traditional x and y graph. Every term, every text, and every novel combination of terms has a high dimensional vector representation. When one compares two terms, one compares the cosine of the angle between the vectors representing the terms (cosine similarity). This occurs within a semantic space. One cannot compare the same word directly between semantic spaces.

Specifically, the cosine similarities from the matrix come from a semantic space titled '1st year college' and have 300 factors. This semantics space was built by Touchstone Applied Science Associates, Inc. (TASA). The texts I used were the 3rd, 6th, 9th, and 12th compulsory texts used in public education. Additionally, there was one category for "college" level. The spaces are cumulative, meaning that the 9th semantic space includes the 3rd and 6th semantic spaces. For more information regarding the semantic spaces, see Laham and Steinhart (2015) or Busemeyer, Zheng, and Whang (2015).

Table 1 shows the subset data that I used for the time-frequency graphics and the cosine comparisons. I extracted these from Laham and Steinhart's (2015) method and represented a sample from the total of 110 Images. This table shows the similarity between two subsampled clustered groups:

Table 1

Cosine similarity for soubgroup of images

		Group 1			Group 2		
		Watch (n = 3 trials)	Rose (n = 3 trials)	Button (n = 2 trials)	Rocket (n = 3 trials)	Plane (n = 2 trials)	Moon (n = 3 trials)
Watch	(n = 3 trials)	1.00	.25	.34	.11	.16	.17
Rose	(n = 3 trials)	.25	1.00	.17	.07	.06	.10
Button	(n = 3 trials)	.34	.17	1.00	.07	.12	.03
Rocket	(n = 3 trials)	.11	.07	.07	1.00	.26	.37
Plane	(n = 2 trials)	.16	.06	.12	.26	1.00	-.01
Moon	(n = 3 trials)	.17	.10	.03	.37	-.01	1.00

Note: All distances are contructed using UC LSA Matrix softwear. The semantic space use was '1st year college with 300 factors'

Hierarchical clustering. In Figure 2, we can see the rearrangement of images into groups or 'clusters' of maximal distance between each other. I performed this rearrangement using an agglomerative hierarchical clustering method, specifically a complete-linkage criteria (1).

(1) $$D(X,Y) = \max_{x \in X, y \in Y} d(x,y)$$

This means that each row (x) is considered its own "cluster" and then paired with the furthest row (y) "cluster" possible. Then, the function 'moves' up a level. In this way, several layers of clusters are made from the bottom up. Since the words were previously selected having a different objective in mind the clustering result generated in this study was not previously thought.

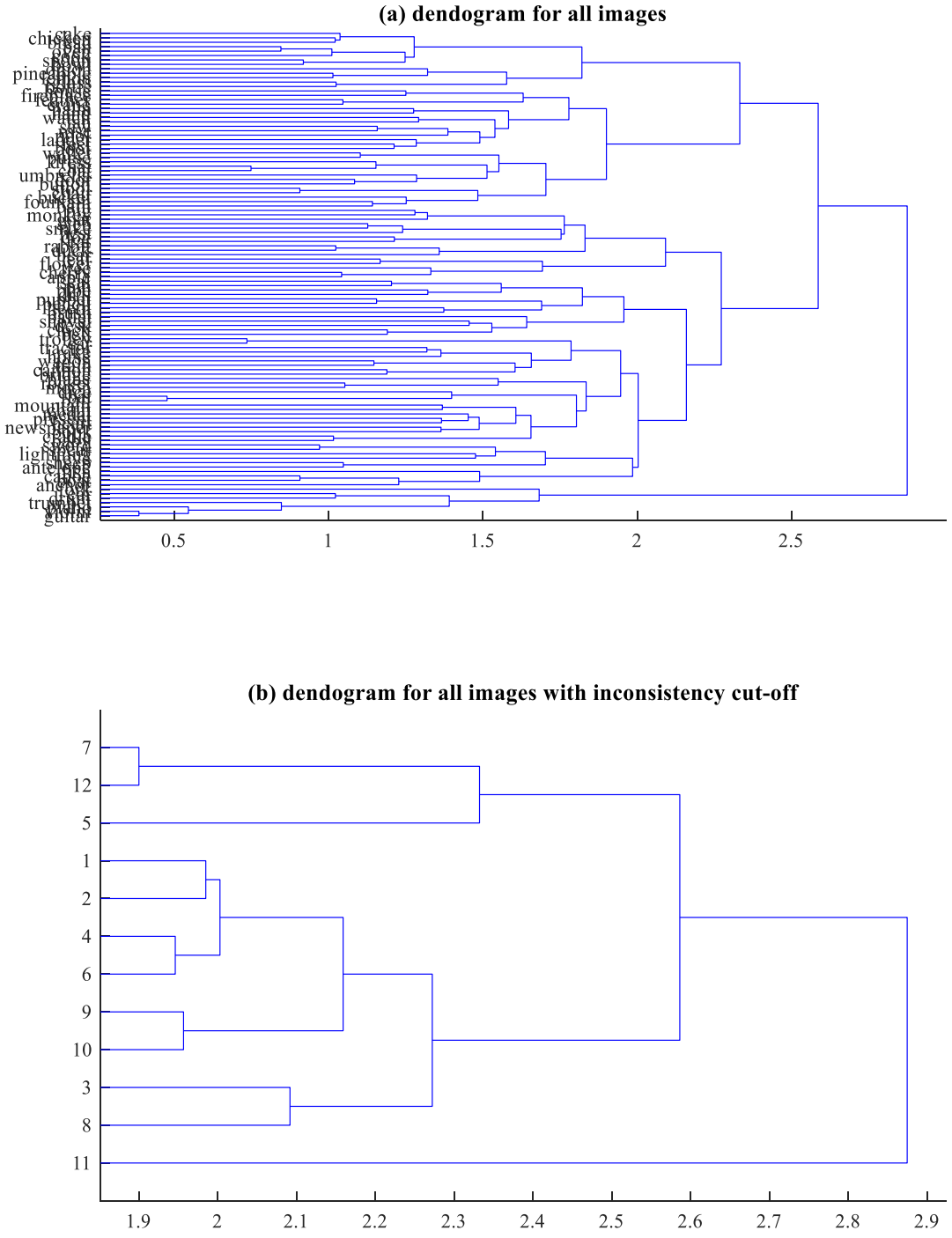


figure 2. **Top** Complete dendogram with the 110 images that the participants saw descripted by words on the left side. **Bottom** 12 clustered groups of images considering a cut-off inconsistency coefficient at 1.95

Statistical analysis. My statistical analysis took the form of a time-frequency analysis. Recent research suggests that there may be rich physiological information embedded within the power spectrum of neurophysiological recordings, which, in addition to power in specific oscillatory frequencies, can be extracted with the appropriate model

(Gao, 2016). To gather spectrum information at the same time that we consider time dynamics, we need to apply to the EEG signal wavelet transformations. In this method, the EEG signal is decomposed into discontinuous oscillating waveforms called wavelets. In mathematics, the wavelet transform refers to the representation of a signal in terms of finite length oscillating waveforms. These waveforms are scaled and translated so that when summed up, they match the input signal. The wavelet function that I used here was the most widely available and used, the Morlet complex function (Kropotov, 2016, p. 31).

By using EEGlab, I implemented the time-frequency analysis with event-related spectral perturbations (ERSP) and inter-trial coherence (ITC) measures (Delorme & Makeig, 2004). Event-related spectral perturbations (ERSP) represent the spectral power difference between the post-stimulus frequency and pre-stimulus baseline frequency. I defined the baseline from -500 ms to the image-sound presentation.

The time-frequency analysis runs from 3 Hz to 125 Hz frequency bands (although it is important to consider that the primary study ran the data through a low-pass filter at 35 Hz, so we will consider only the frequencies under that value). I analysed the frequencies in 0.3 Hz increments using a sliding hanning-windowed 3-cycle sinusoidal wavelet transform of the time-domain signal with a step size of 5 ms.

When we build a wavelet and perform spectral analysis on time series, the spectrum reveals the frequency components of the signal. Since spectrum analysis considers the hole time domain epoch, it is uncertain where the frequency is allocated in time. To increase the time resolution one could reduce the epoch of the input signal. Nevertheless, this time reduction necessarily affects resolution of the spectral analysis. The time-frequency resolution means that there exists a trade-off between frequency and time resolution. I decided to divide every epoch into 100 frequencies and a 100 times (van Drongelen, 2018, p. 430).

Results

Collected and Baseline Data and Subsets

The study uses two sources of data: (1) a semantic distribution for 110 image-sounds and (2) the 73 EEG recordings for healthy elderly participants. There were three baseline datasets from which to develop an analysis.

i) I conducted the first analyses over a grand average for all 73 participants without artefact removal. This included the 270 images that every participant saw. The final grand average base of individually considered trials amounted to a total of 19,710 trials.

ii) The second included the 73 participants after using the primary study artefact removal technique. After taking away the 4,877 noisy trials, the final amount of trials I considered is 14,833. Thus, on average, I had removed 18 (SD = 4.40) trials per image-sound. When testing for normality using a one-sample Kolmogorov-Smirnov test, I rejected the null hypothesis of a normal distribution at the 5% significance level. The distribution seems to skew slightly to the right. Those image-sounds that I removed more times than a normal distribution would suggest were a puppet (removed 38 times), a violin (removed 34 times), a flower (removed 33 times), and chair (removed 31 times). The only image that may be accountable for its position is the puppet because it is presented first. The violin, flower, and chair are presented as one followed by the other.

ii) I finished the third sub-datasets whilst using ITC and the ERSP in EEGlab in order to visualise the differences between semantic groups. This sub-dataset contains two conditions that included three images each (Group 1: Violin, Guitar, Piano; Group 2: Stool, Bucket, Saw). The first arrangement contained 426 trials, and the second arrangement contained 336 trials, adding to a total of 752 trials. The criteria for selection were that all images belong to the same cluster and that the clusters were as far apart as possible from each other in time.

iii) I sub-grouped all datasets by electrodes of interest.

Relevant Results

Behavioural results. When using the primary dataset trial types (New, Old/Short, Old/Long), the responses across stimuli seem stable on RT (F (2,268) = 19.69, $p < .001$), with a decrease from 1209 ms in the New condition to 1148 ms and 1114 ms in Old/Short and Old/Long conditions, respectively. Error rates did not differ significantly between memory conditions (F (2,268) = 1.4, *ns*) and neither did miss rate (F (2,268) = 2.04, *ns*). Moreover, group and memory did not interact with respect to RT (F (2,268) =.19, *ns*) or error rate (F (2,268) = .42, *ns*).

Hierarchical clustering. With Matlab 2018a Update 3, I ran an agglomerative cluster tree to the similarity matrix previously obtained from the LSA software. The similarity measures I used were cosine distances. As I stated in the method section, the clustering method was a complete linkage one, also called farthest neighbour. The cut off for the number of clusters I selected was an inconsistency coefficient no greater than 1.95. That resulted in 12 clusters.

Time/frequency group differences. I defined the mapping area by considering a -500 millisecond baseline and a limit of 1000 milliseconds after the presented image-sound. The frequencies analysed are all between 3 Hz and 35 Hz. All ERPS and ITC reacted by electrodes together at the same time, making a selection. The units shown in the graphic are decibels (dB). Results here show a difference in oscillatory response when grouped by different semantic distribution clusters. I consider 4 groups of electrodes named after the region of the brain region where they were placed (e.g., occipital, right central, left central, and others).

The right central electrodes are the first group for analysis. The names of these electrodes are E106, E107, E113, and E112. As seen in Figure 3, the event-related response seems to have a narrow difference between the two conditions. One point was the

ERP difference is particularly salient is at the P3a component. Therefore, at first glance, they do not support the hypothesis of different physiological responses conditioned to distributional semantic modelling. Next, for electrode E107, the ERSP results for the two groups shows a much bigger difference in terms of oscillations, between 7 Hz and 13 Hz from 300 ms onwards, suggesting an increase in alpha activity in the 'Rocket' condition over the 'Button' condition. A smaller difference was still noticeable, which shows an increase in theta activity from the 400 ms onwards.

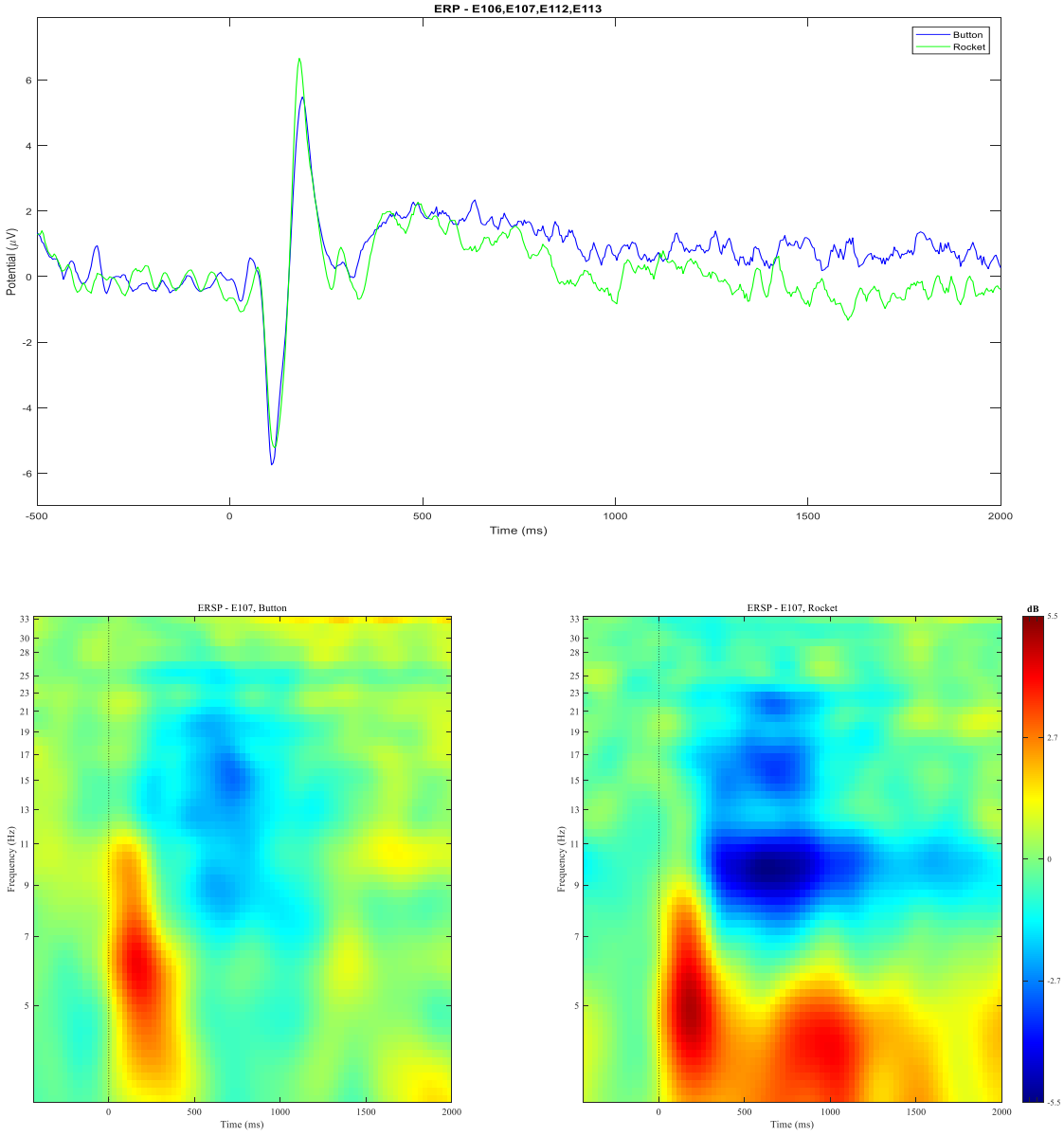
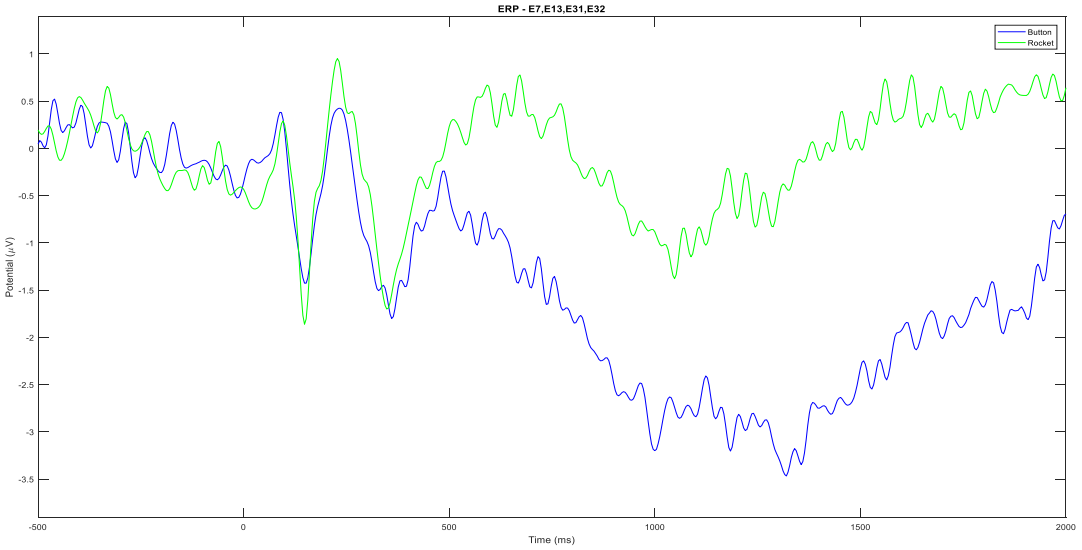


Figure 3. **Top.** Central electrodes ERP response divided into two conditions previously explained, 'Button' and 'Rocket' for all 73 participants. **Bottom** ERSP for electrode E107 compared into two conditions.

The next four electrodes are on the left hemisphere. The electrode names are E7, E13, E31, and E32. The visual results of the event-related potential component of this group start later and with a positive shift. I believe this component forms part of the P300 (Polich, 2007). The ERSP in Figure 4, using E7 as an example, shows from 300 ms onwards more alpha activity (7 Hz - 11 Hz) in the ‘Rocket’ group than in the ‘Buttons’ group. This is consistent with the ‘Rocket’ group taking the upper side of the ERP response graph. These results are in line with the results from the right central electrodes in the previous figure.



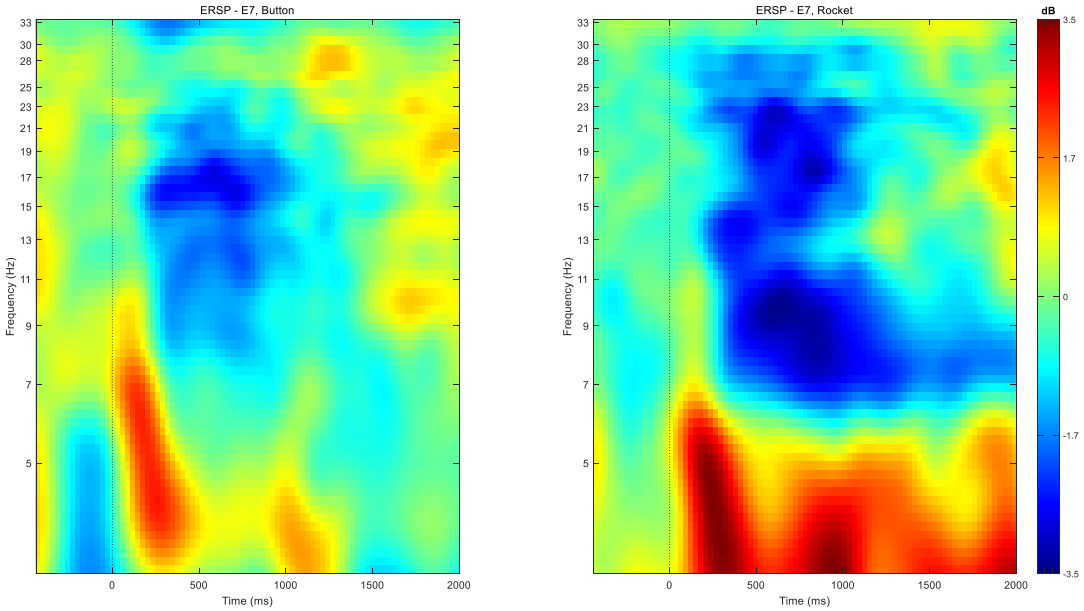


figure 4. **Top.** Left hemisphere central electrodes ERP response divided into two conditions previously explained, 'Button' and 'Rocket' for all 73 participants. **Bottom** ERSP for electrode E7 compared into two conditions considering all participants.

The occipital electrodes, named E53, E60, E86, and E87, show a difference between 500 ms and 700 ms. For the ERSP analysis the electrode E87 - here used as an example but observable in the other electrodes as well - shows a decrease in alpha oscillations (9 Hz) in the 'Rocket' group whereas it shows a decrease in low beta (16 Hz) oscillations in the 'Button' group.

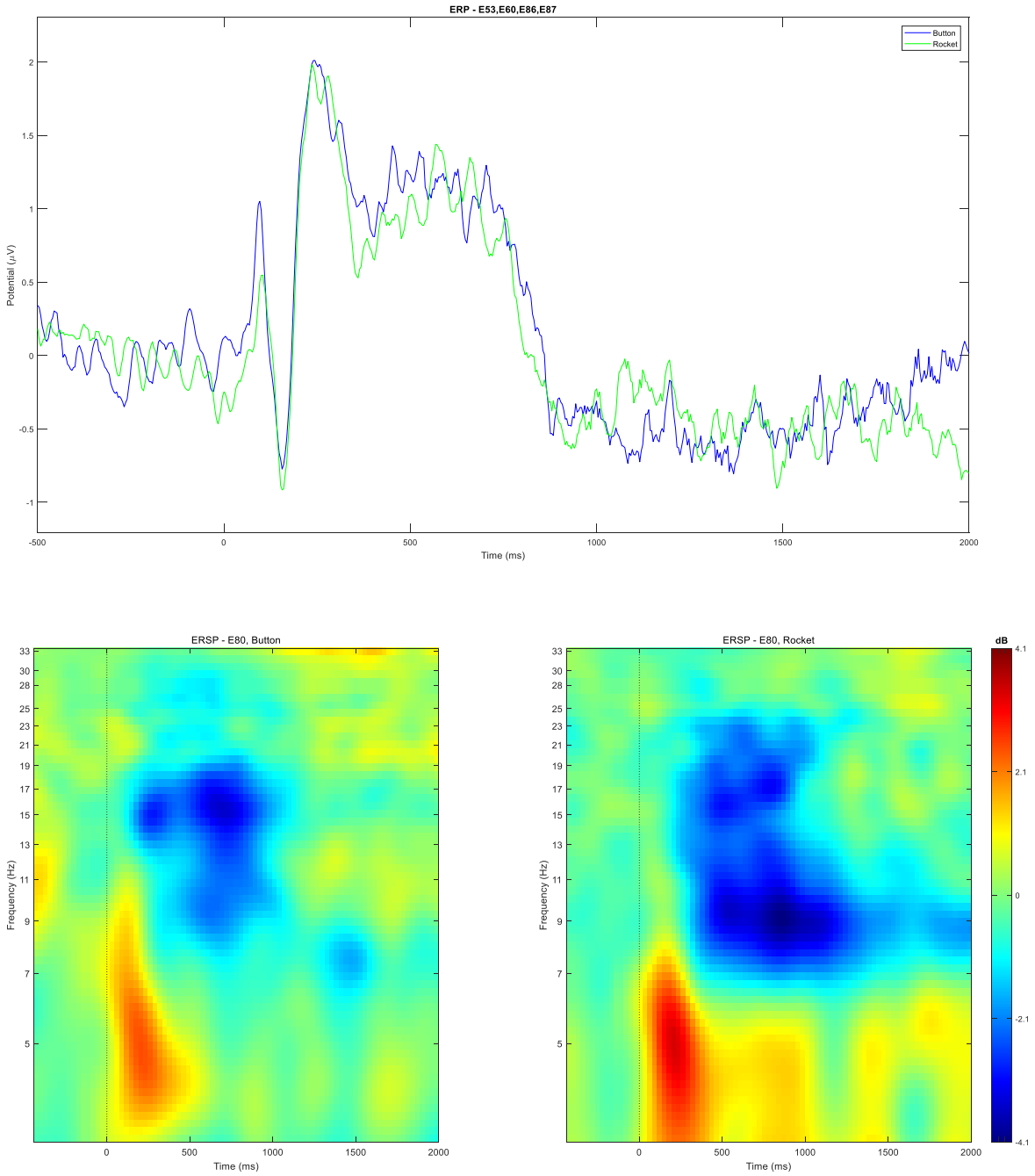


figure 5 **Top.** Occipital electrodes ERP response divided into two conditions previously explained, 'Button' and 'Rocket' for all 73 participants. **Bottom.** ERSP for electrode E80 compared between two conditions.

Although all previous results should be interpreted with care and as a visual exploration since they have not yet been tested (Diepen & Mazaheri, 2018, p. 6), it is important to stress that these findings are consistent with Klimesch's (1999) findings in which alpha and theta oscillations decrease and increase, respectively, after a memory-triggering event.

Representational Similarity Analysis Results

Here, I show the extent to which the brain-data representational similarity matrix from the brain fits the representational similarity matrix built from the images cosine comparison matrix. I performed all computations considering the period between 0 and 500 ms after the images-sound semantic representations. When considering from the event onset (0) until one second the first second after the mean correlation improved for all electrodes considered together. There are significant results for the clustered data in central electrodes for both hemispheres after correcting for multiple comparisons (random effect, $p < 0.015$). When considering the occipital area, I found that the results were not significant. These results show that for central electrodes that the semantic space of image-sound representation has a significant effect on the representation of brain data. The coming overview of effects is shown in Figures 6, 7, 8, and 9.

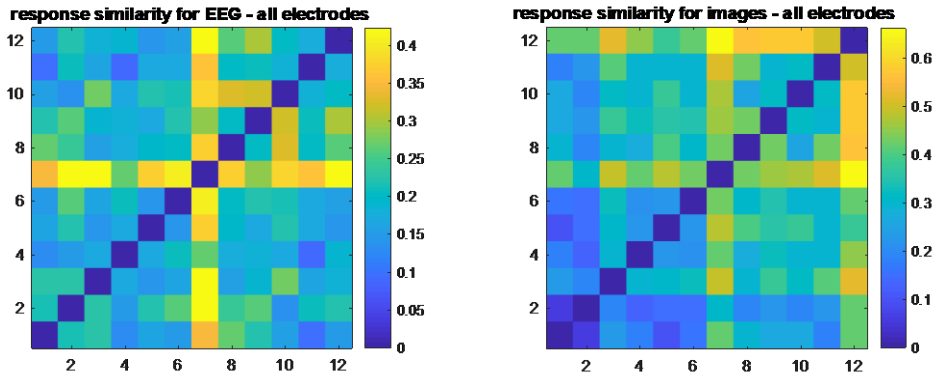


figure 6. The mean correlation between the semantic similarity matrix and the representational similarity matrix is .16 (SD = .22, random effect, $p <$ .05).

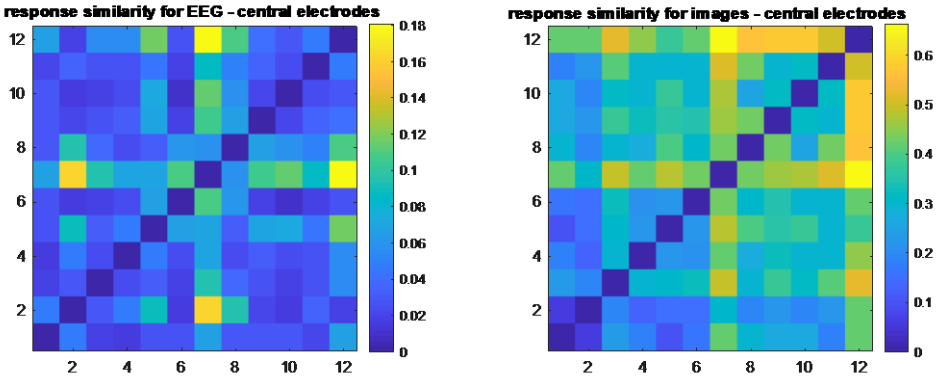


figure 7. Among the right central electrodes, the mean correlation between the semantic similarity matrix and the representational similarity matrix is .25 (SD = .07; random effect, $p < .015$).

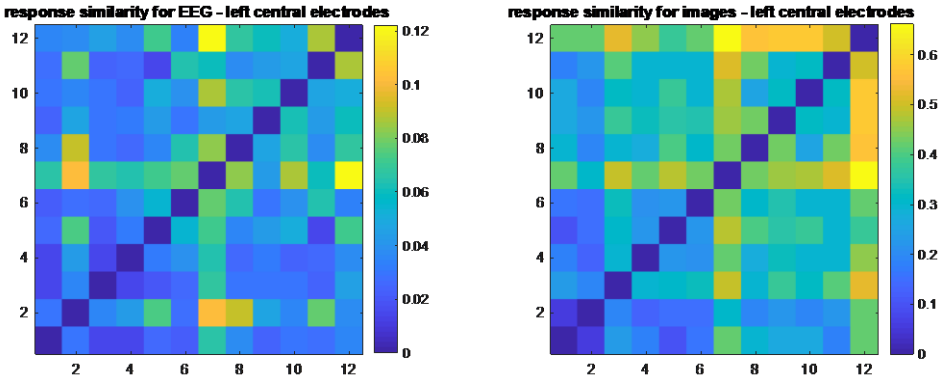


figure 8. The left central electrodes have a mean correlation between the semantic similarity matrix and the representational similarity matrix of .21 (SD = .07; random effect, $p < .015$).

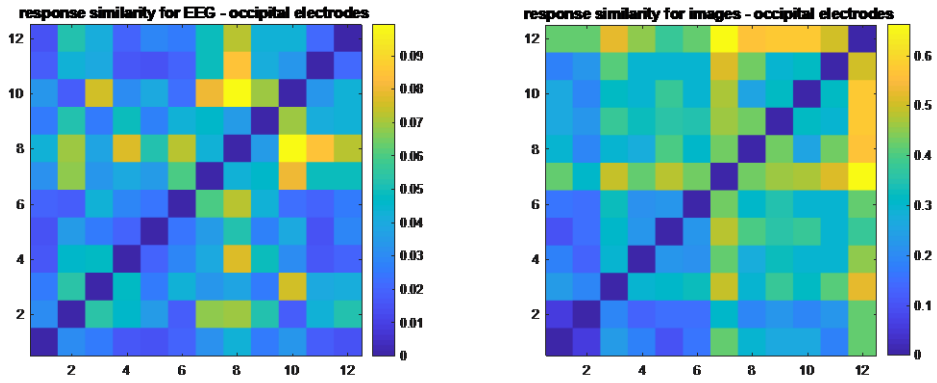


figure 9. Occipital electrodes have a mean correlation between the semantic similarity matrix and the representational similarity matrix of .08 (SD = .05; random effect, ns).

Discussion

I found consistent evidence showing a relationship between the representations of the distributional semantic model and the physiological representations of the brain response. With all electrodes considered in a grand average, the correlation proves significant at the 5% level in a multiple comparison random test. The relationship was stronger for central electrodes at a 1.5% significance level and was smaller and not significant for occipital electrodes.

The alpha and beta suppression registered in the ERSP maps is in line with the findings of previous studies on attentional levels and memory loads (Shahin, Picton, & Miller, 2009; Bastiaansen, van der Linden, Ter Keur, Dijkstra, & Hagoort, 2005; Klimesch, 1999). This finding is also in line with findings on memory search or memory scanning demands - which also show alpha suppression (Kaufman, Curtis, Wang, & Williamson, 1992; Rojas, Teale Sheeder, & Reite, 2000). It would be interesting for future research to prove whether more frequent – or easy to remember – semantic clusters have less intense alpha or theta frequency suppression after they been presented. It could be that less frequent semantic representations elicit more alpha power decrease (memory effort) and more theta power increase (encoding effort). This could have implications for memory tests.

A possible interpretation for these results is that certain brain regions consistently activate when the participants recall different semantic groups. In other words, there could be an interconnection between the electrical response and the theoretical semantic space position in the overall picture of the brain. This is in line with previous findings by Huth et al., which establish representations of meaning at the level of the word, where his team was able to construct complex maps across the association cortex (Huth, de Heer, Griffiths, Theunissen, & Gallant, 2016). A particularity of this dissertation is that the representations of meaning were presented to the participants in the form of image-sounds.

In Huth's study, the participants heard a story. This similarity could mean that representations of meaning are accessed in the same way, independently of the modality of the study.

According to Huth et al., the medial prefrontal cortex is predicted to activate when retrieving semantic memories associated with mental, social and/or temporal heard words. This results points towards signalling that the brain electrical response is related to the visual-auditory semantic representation a participant is exposed to. Therefore, this study along with previous semantic mapping efforts, open up the possibility to try identify localized memory disorders by recalling different semantic groups, while sensing with EEG. For example, logogenic primary aphasia (a variant of AD) normally shows a different brain response - as measured by a fMRI - on the right working memory system (Witwell et al., 2014). Consequently, we could test differences in elicited electrical responses by exposing patients to targeted semantic groups (e.g. mental, social, temporal).

Working with secondary data presents a new set of challenges. Even if most steps in data processing are explained, in some instances assumptions are still required. The most important assumption I made was on how the images were distributed – given that EEG data came sorted by type of response (e.g. NewC short, OldC short, etc.). In the end, this assumption proved to be correct since all correct or incorrect responses were found on the 19.710 trials assumed distribution. Another challenge I found working with secondary data was the fact that epochs came arranged in fix sorting. This meant I could not develop an artefact removal process neither a filtering process – thus being unable to study frequencies over 35 Hz.

The non-significant results for the occipital electrodes can be accounted for in previous findings. Other researchers have found that the occipital area plays a role in visual selective attention that is captured by the occipital electrodes (Heinze, Mangun, Burchert, Hinrichs, Scholz, Munte, Gos, et al., 1994; Cabeza & Nyberg, 2000). The ERP

response in figure 6 seems suggest that the visual role of the occipital electrodes is more prominent than the semantic memory role when compared both together. We can expect no difference between semantic representations. When images are presented regardless of their semantic content, they are visually attended in the same way by this area.

The virtue of grand averages is that when the sample is sufficiently big, different noise components of the signal start counteracting with each other and add up to a 0 mean if we assume normality in the noise distribution. A downside to this approach is in the fact that it is harder to observe for individual variabilities across participants. Also in Huth et al.'s (2016) recent work, he found consistency in the mapping across individuals.

Multivariate pattern analysis (MVP) in cognitive neuroscience should be treated carefully. Neural decoding, as done by non-linear mathematical models, assumes that if information can be decoded from patterns of neural activity, then those patterns present enough evidence (e.g., King & Dehane, 2014). Ritchie, Kaplan and Klein (2017) critique this approach from a philosophical standpoint. They claim that MVPA might be too powerful: "It allows for information that is in the brain but could not be exploited by the brain itself" (p. 13). As a recommendation, they stress the need to blend the decoding results with behavioural and psychological models of human conduct. Bridging the existing technique and knowledge in MVPA, AD and memory theoretical models could prove helpful to improving all three matters simultaneously, although it is critical to find and use connection points correctly.

Future research should continue to build a bridge between atypical AD phenotypes by distinguishing semantic distribution patterns and establishing their relation between EEG markers and cognitive decline.

References

Van Drongelen, W. (2007). *Signal Processing for Neuroscientists*. *Signal Processing for Neuroscientists*. Elsevier Inc. https://doi.org/10.1016/B978-0-12-370867-0.X5000-1

Gallego-Jutglà, E., Solé-Casals, J., Vialatte, F.-B., Dauwels, J., & Cichocki, A. (2014). A Theta-Band EEG Based Index for Early Diagnosis of Alzheimer's Disease. *Journal of Alzheimer's Disease : JAD*, *43*, 1175–1184. https://doi.org/10.3233/JAD-140468

Cummings JL. Alzheimer's disease. N Engl J Med 2004; 351: 56–67

Alzheimer's Association. (2017). *2017 Alzheimer's Disease Facts and Figures*. *Alzheimers Dement* (Vol. 13, pp. 325–373). https://doi.org/10.1016/j.jalz.2017.02.001

Alzheimer's Association. (2017). *2017 Alzheimer's Disease Facts and Figures*. *Alzheimers Dement* (Vol. 13, pp. 325–373). https://doi.org/10.1016/j.jalz.2017.02.001

Phillips, J. S., Das, S. R., McMillan, C. T., Irwin, D. J., Roll, E. E., Da Re, F., … Grossman, M. (2018). Tau PET imaging predicts cognition in atypical variants of Alzheimer's disease. *Human Brain Mapping*, *39*(2), 691–708. https://doi.org/10.1002/hbm.23874

Cummings, J. L. (2004). Alzheimer's Disease. *New England Journal of Medicine*, *351*(1), 56–67. https://doi.org/10.1056/NEJMra040223

McKhann, G., Drachman, D., Folstein, M., Katzman, R., Price, D., & Stadlan, E. M. (1984). Clinical diagnosis of Alzheimer's disease: Report of the NINCDS-ADRDA Work Group* under the auspices of Department of Health and Human Services Task Force on Alzheimer's Disease. *Neurology*, *34*(7), 939–939. https://doi.org/10.1212/WNL.34.7.939

Dubois, B., Feldman, H. H., Jacova, C., Hampel, H., Molinuevo, J. L., Blennow, K., … Cummings, J. L. (2014). Advancing research diagnostic criteria for Alzheimer's disease: The IWG-2 criteria.

The Lancet Neurology. Lancet Publishing Group. https://doi.org/10.1016/S1474-4422(14)70090-0

Cummings, J. L., Dubois, B., Molinuevo, J. L., & Scheltens, P. (2013, May). International Work Group Criteria for the Diagnosis of Alzheimer Disease. *Medical Clinics of North America*. https://doi.org/10.1016/j.mcna.2013.01.001

Tulving, E. (1972). Episodic and semantic memory 1. *Organization of Memory*, (24171), 381–403.

Craik, F. I., & McDowd, J. M. (1987). Age differences in recall and recognition. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *13*(3), 474–479. https://doi.org/10.1037/0278-7393.13.3.474

Dubois, B., Feldman, H. H., Jacova, C., Hampel, H., Molinuevo, J. L., Blennow, K., … Cummings, J. L. (2014). Advancing research diagnostic criteria for Alzheimer's disease: The IWG-2 criteria. *The Lancet Neurology*. Lancet Publishing Group. https://doi.org/10.1016/S1474-4422(14)70090-0

Dubois, B., & Albert, M. L. (2004, April 1). Amnestic MCI or prodromal Alzheimer's disease? *Lancet Neurology*. https://doi.org/10.1016/S1474-4422(04)00710-0

Schneider, J. A., Wilson, R. S., Bienias, J. L., Evans, D. A., & Bennett, D. A. (2004). Cerebral infarctions and the likelihood of dementia from Alzheimer disease pathology. *Neurology*, *62*(7), 1148–1155. https://doi.org/10.1212/01.WNL.0000118211.78503.F5

Busemeyer, J. R. [Ed], Wang, Z. [Ed], Townsend, J. T. [Ed], & Eidels, A. [Ed]. (2015). The Oxford handbook of computational and mathematical psychology. *The Oxford Handbook of Computational and Mathematical Psychology*.https://doi.org/10.1024/1661-4747.54.1.68a

Aggleton, J. P., & Brown, M. W. (1999). Episodic memory, amnesia, and the hippocampal-anterior thalamic axis. *Behavioral and Brain Sciences*. https://doi.org/10.1017/S0140525X99002034

Cabeza, R., Ciaramelli, E., Olson, I. R., & Moscovitch, M. (2008, August). The parietal cortex and episodic memory: An attentional account. *Nature Reviews Neuroscience*. https://doi.org/10.1038/nrn2459

Greenberg, D. L., & Verfaellie, M. (2010). Interdependence of episodic and semantic memory: evidence from neuropsychology. *Journal of the International Neuropsychological Society : JINS*, *16*(5), 748–53. https://doi.org/10.1017/S1355617710000676

Andrews, M., Vigliocco, G., & Vinson, D. (2009). Integrating Experiential and Distributional Data to Learn Semantic Representations. *Psychological Review*, *116*(3), 463–498. https://doi.org/10.1037/a0016261

Wittgenstein, L. (1953). *Philosophical Investigations*. *The American Journal Of Bioethics Ajob*(Vol. 34, pp. 48–52). https://doi.org/10.1111/j.1365-2648.2010.05545.x

Firth, J. R. (1957). A synopsis of linguistic theory, 1930-1955. In *Studies in Linguistic Analysis*(pp. 1–32). Blackwell. Retrieved from http://annabellelukin.edublogs.org/files/2013/08/Firth-JR-1962-A-Synopsis-of-Linguistic-Theory-wfihi5.pdf

J., D., F., V., & A., C. (2010). Diagnosis of Alzheimer's disease from EEG signals: Where are we standing? *Current Alzheimer Research*, *7*(6), 487–505. Retrieved from http://www.embase.com/search/results?subaction=viewrecord&from=export&id=L359998880

Horvath, A., Szucs, A., Csukly, G., Sakovics, A., Stefanics, G., & Kamondi, A. (2018). EEG and ERP biomarkers of Alzheimer's disease: a critical review. *Frontiers in Bioscience (Landmark Edition)*, *23*, 183–220. https://doi.org/http://dx.doi.org/10.2741/4587

Zhang, H., Watrous, A. J., Patel, A., & Jacobs, J. (2018). Theta and Alpha Oscillations Are Traveling Waves in the Human Neocortex. *Neuron*, *98*(6), 1269–1281.e4. https://doi.org/10.1016/j.neuron.2018.05.019

Shahin, A. J., Picton, T. W., & Miller, L. M. (2009). Brain oscillations during semantic evaluation of speech. *Brain and Cognition*, *70*(3), 259–266. https://doi.org/10.1016/j.bandc.2009.02.008

Su, L., Fonteneau, E., Marslen-Wilson, W., & Kriegeskorte, N. (2012). Spatiotemporal searchlight representational similarity analysis in EMEG source space. In *Proceedings - 2012 2nd International Workshop on Pattern Recognition in NeuroImaging, PRNI 2012*(pp. 97–100). https://doi.org/10.1109/PRNI.2012.26

King, J. R., & Dehaene, S. (2014). Characterizing the dynamics of mental representations: The temporal generalization method. *Trends in Cognitive Sciences*. Elsevier Ltd. https://doi.org/10.1016/j.tics.2014.01.002

Chan, A. M., Halgren, E., Marinkovic, K., & Cash, S. S. (2011). Decoding word and category-specific spatiotemporal representations from MEG and EEG. *NeuroImage*, *54*(4), 3028–3039. https://doi.org/10.1016/j.neuroimage.2010.10.073

Turner, W. F., Johnston, P., de Boer, K., Morawetz, C., & Bode, S. (2017). Multivariate pattern analysis of event-related potentials predicts the subjective relevance of everyday objects. *Consciousness and Cognition*, *55*, 46–58. https://doi.org/10.1016/j.concog.2017.07.006

Cichy, R. M., & Pantazis, D. (2017). Multivariate pattern analysis of MEG and EEG: A comparison of representational structure in time and space. *NeuroImage*, *158*, 441–454. https://doi.org/10.1016/j.neuroimage.2017.07.023

Kriegeskorte, N., & Kievit, R. A. (2013, August). Representational geometry: Integrating cognition, computation, and the brain. *Trends in Cognitive Sciences*. https://doi.org/10.1016/j.tics.2013.06.007

Palmeri, T. J., Love, B. C., & Turner, B. M. (2017, February 1). Model-based cognitive neuroscience. *Journal of Mathematical Psychology*, *76*, 59–64. https://doi.org/10.1016/j.jmp.2016.10.010

Boekel, W., Forstmann, B. U., & Wagenmakers, E. J. (2016, January 1). Challenges in replicating brain-behavior correlations: Rejoinder to Kanai (2015) and Muhlert and Ridgway (2015). *Cortex*. Masson SpA. https://doi.org/10.1016/j.cortex.2015.06.018

Kerry W. Kilborn, Zoë Tieges, Jessica Price, Susil Stephen, Bernard A. Conway, Delphine Duclap, Alan H. Hughes, Gillian McLean (2010). Source localization of event-related potential effects differentiates between vascular dementia and Alzheimer's disease. *Alzheimer's & Dementia* vol. 6 issue 4, Elsevier

Vigliocco, G., & Vinson, D. P. (2012). *Semantic representation*. *The Oxford Handbook of Psycholinguistics*. https://doi.org/10.1093/oxfordhb/9780198568971.013.0012

WMA. (1974). *Declaration of Helsinki. Lance* (Vol. 353, pp. 1418–1419). https://doi.org/10.2471/BLT.08.057737

Christie, B. (2000). Doctors revise declaration of Helsinki. *BMJ (Clinical Research Ed.)*, *321*(7266), 913. https://doi.org/10.1136/bmj.321.7266.913

Tucker, D. M. (1993). Spatial sampling of head electrical fields: the geodesic sensor net. *Electroencephalography and Clinical Neurophysiology*, *87*(3), 154–163. https://doi.org/10.1016/0013-4694(93)90121-B

Delorme, A., & Makeig, S. (2004). EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, *134*(1), 9–21. https://doi.org/10.1016/j.jneumeth.2003.10.009

Gallego-Jutglà, E., Elgendi, M., Vialatte, F., Solé-Casals, J., Cichocki, A., Latchoumane, C., … Dauwels, J. (2012). Diagnosis of Alzheimer's disease from EEG by means of synchrony measures in optimized frequency bands. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*(pp. 4266–4270). https://doi.org/10.1109/EMBC.2012.6346909

Dave Steinhart - *Cross Language Retrieval* and *Summarize!* demonstrations (2015). Website modified on 2015. - http://lsa.colorado.edu/

Kropotov, J. D. (2016). *Functional Neuromarkers for Psychiatry: Applications for Diagnosis and Treatment*. *Functional Neuromarkers for Psychiatry: Applications for Diagnosis and Treatment* (pp. 1–462). Elsevier Inc. https://doi.org/10.1016/C2012-0-07144-X

Van Diepen, R. M., & Mazaheri, A. (2018). The Caveats of observing Inter-Trial Phase-Coherence in Cognitive Neuroscience. *Scientific Reports*, *8*(1). https://doi.org/10.1038/s41598-018-20423-z

Klimesch, W. (1999, April). EEG alpha and theta oscillations reflect cognitive and memory performance: A review and analysis. *Brain Research Reviews*. https://doi.org/10.1016/S0165-0173(98)00056-3

Shahin, A. J., Picton, T. W., & Miller, L. M. (2009). Brain oscillations during semantic evaluation of speech. *Brain and Cognition*, *70*(3), 259–266. https://doi.org/10.1016/j.bandc.2009.02.008

Bastiaansen, M. C. M., Van Der Linden, M., Ter Keurs, M., Dijkstra, T., & Hagoort, P. (2005). Theta responses are involved in lexical-semantic retrieval during language processing. *Journal of Cognitive Neuroscience*, *17*(3), 530–541. https://doi.org/10.1162/0898929053279469

Polich, J. (2007, October). Updating P300: An integrative theory of P3a and P3b. *Clinical Neurophysiology*. https://doi.org/10.1016/j.clinph.2007.04.019

Kaufman, L., Curtis, S., Wang, J. Z., & Williamson, S. J. (1992). Changes in cortical activity when subjects scan memory for tones. *Electroencephalography and Clinical Neurophysiology*, *82*(4), 266–284. https://doi.org/10.1016/0013-4694(92)90107-S

Rojas, D. C., Teale, P. D., Sheeder, J. L., & Reite, M. L. (2000). Neuromagnetic alpha suppression during an auditory Sternberg task - Evidence for a serial, self-terminating search of short-term memory. *Cognitive Brain Research*, *10*(1–2), 85–89. https://doi.org/10.1016/S0926-6410(00)00026-4

Huth, A. G., De Heer, W. A., Griffiths, T. L., Theunissen, F. E., & Gallant, J. L. (2016). Natural speech reveals the semantic maps that tile human cerebral cortex. *Nature*, *532*(7600), 453–458. https://doi.org/10.1038/nature17637

Heinze, H. J., Mangun, G. R., Burchert, W., Hinrichs, H., Scholz, M., Münte, T. F., … Hillyard, S. A. (1994). Combined spatial and temporal imaging of brain activity during visual selective attention in humans. *Nature*, *372*(6506), 543–546. https://doi.org/10.1038/372543a0

Demeter, E., Hernandez-Garcia, L., Sarter, M., & Lustig, C. (2011). Challenges to attention: A continuous arterial spin labeling (ASL) study of the effects of distraction on sustained attention. *NeuroImage*, *54*(2), 1518–1529. https://doi.org/10.1016/j.neuroimage.2010.09.026

Ritchie, J. B., Kaplan, D., & Klein, C. (2017). Decoding The Brain: Neural Representation and The Limits Of Multivariate Pattern Analysis In Cognitive Neuroscience. *BioRxiv*, 127233.Ahttps://doi.org/10.1101/127233

Whitwell, J. L., Jones, D. T., Duffy, J. R., Strand, E. A., Machulda, M. M., Przybelski, S. A., … Josephs, K. A. (2015). Working memory and language network dysfunctions in logopenic aphasia: A task-free fMRI comparison with Alzheimer's dementia. *Neurobiology of Aging*, *36*(3), 1245–1252. https://doi.org/10.1016/j.neurobiolaging.2014.12.013

Gao, R. (2016). Interpreting the electrophysiological power spectrum. *Journal of Neurophysiology*, *115*(2), 628–630. https://doi.org/10.1152/jn.00722.2015