

The electrophysiological correlates of word pre-activation during associative word learning

Stefan Elmer^{a,b,*}, Mireille Besson^e, Antoni Rodríguez-Fornells^{b,c,d}

^a Computational Neuroscience of Speech & Hearing, Department of Computational Linguistics, University of Zurich, Switzerland

^b Cognition and Brain Plasticity Group, Bellvitge Biomedical Research Institute, L'Hospitalet de Llobregat, 08097 Barcelona, Spain

^c Department of Cognition, Development and Educational Psychology, Campus Bellvitge, University of Barcelona, L'Hospitalet de Llobregat, 08097 Barcelona, Spain

^d Institució Catalana de Recerca i Estudis Avançats, ICREA, 08010 Barcelona, Spain

^e Université Publique de France, CNRS & Aix-Marseille University, Laboratoire de Neurosciences Cognitives (LNC, UMR 7291) & Institute for Language and Communication in the Brain (ILCB), Marseille, France

ARTICLE INFO

Keywords:

EEG
N200
N400
LPC
Pre-activation
Word learning

ABSTRACT

Human beings continuously make use of learned associations to generate predictions about future occurrences in the environment. Such memory-related predictive processes provide a scaffold for learning in that mental representations of foreseeable events can be adjusted or strengthened based on a specific outcome. Learning the meaning of novel words through picture-word associations constitutes a prime example of associative learning because pictures preceding words can trigger word prediction through the pre-activation of the related mnemonic representations. In the present electroencephalography (EEG) study, we used event-related potentials (ERPs) to compare neural indices of word pre-activation between a word learning condition with maximal prediction likelihood and a non-learning control condition with low prediction. Results revealed that prediction-related N400 amplitudes in response to pictures decreased over time at central electrodes as a function of word learning, whereas late positive component (LPC) amplitudes increased. Notably, N400 but not LPC changes were also predictive of word learning performance, suggesting that the N400 component constitutes a sensitive marker of word pre-activation during associative word learning.

1. Introduction

The human brain constantly generates predictions about future events based on past experience, learned associations or statistical regularities in the environment (Bar, 2009; Benitez and Saffran, 2018). Such predictive processes have been shown to play an essential role in learning in many domains, including perception (Emberson et al., 2015), motor control (Flanagan et al., 2003) and feedback expectation (Moris et al., 2013). Furthermore, many authors highlighted the importance of prediction for language learning (Reuter et al., 2019) and language processing in general (Chang et al., 2006; Dell and Chang, 2014; DeLong et al., 2005; Elman, 1991; Leon-Cabrera et al., 2019; Pickering and Garrod, 2014). One of the benefits of prediction for learning is that the discrepancy between an expected and an actual sensory input leads to a prediction error that can be used to update a mental model, redirect attention toward new sources of information or

adjust future expectations (Schultz and Dickinson, 2000). Furthermore, a close correspondence between prediction and outcome acts as a positive feedback that strengthens prediction consistency and consolidates learning (Ganzach, 1994).

Building associations between items has long been recognized as a fundamental principle of learning, and constitutes the basis of episodic memory and long-term retention (Bar, 2009; Schultz and Dickinson, 2000). Given that during associative learning the activation of one item can trigger the mnemonic representation of the related element, predictive processes are inextricably linked to memory (Bar, 2009). Drawing on this background, learning the meaning of novel words through picture-word associations (Dittinger et al., 2016; Dittinger et al., 2017; Dobel et al., 2009) is a prime example of associative learning that opens up the possibility of examining the neural basis of predictive processes. In particular, based on previous EEG studies that provided empirical evidence for the suitability of the auditory N200,

* Corresponding author at: Department of Computational Linguistics, Computational Neuroscience of Speech & Hearing, University of Zurich, Andreasstrasse 15, 8050 Zurich, Switzerland.

E-mail addresses: stefan.elmer@uzh.ch (S. Elmer), mireille.besson@univ-amu.fr (M. Besson), arfornells@gmail.com (A. Rodríguez-Fornells).

<https://doi.org/10.1016/j.ijpsycho.2022.09.007>

Received 28 July 2022; Received in revised form 14 September 2022; Accepted 21 September 2022

Available online 24 September 2022

0167-8760/© 2022 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

N400 and LPC components as biomarkers of word learning (Bakker et al., 2015; Borovsky et al., 2010; de Diego-Balaguer et al., 2016; Dittinger et al., 2016; Dittinger et al., 2017; Francois et al., 2017; Mestres-Misse et al., 2007; Takashima et al., 2017; Zwitserlood et al., 2018), one would expect that the same EEG indices are likewise sensitive to the pre-activation of learned words in response to pictures preceding the associated words. This perspective is based on the assumption that if a specific component is involved in tracking particular aspects of auditory word learning (e.g., phonological categorization, lexical-semantic processing, etc.), then memory-related pre-activation of determined features should principally be manifested in a modulation of the same ERPs. Such a top-down modulation of auditory-related ERPs has been shown, for example, for both the imagery of syllables and musical items (Meyer et al., 2007). Furthermore, during word learning, these ERP components typically shift along an anterior-posterior topographical axis, with frontal manifestations at early stages of word learning and posterior distributions when learning is stabilized (Bakker et al., 2015; Borovsky et al., 2010; Dittinger et al., 2016; Dittinger et al., 2017; Elmer et al., 2021). Importantly, since faithful predictions rely on the retrieval of already learned associations, one would expect that genuine predictive processes are most likely detectable at central and posterior scalp sites.

From a neurolinguistics perspective, the N400 component is particularly sensitive to semantic deviance, and its amplitude increases with the processing costs of lexical-semantic retrieval (Borovsky et al., 2010; Brouwer et al., 2012; DeLong et al., 2005; Kutas and Federmeier, 2011; Lau et al., 2009; Lau et al., 2008; Van Berkum, 2009, 2010). Accordingly, N400 amplitudes are usually larger in response to pseudowords than to words, to infrequent compared to frequent words, to concrete than to abstract words, and to nouns that do not fit into a phrasal context (DeLong et al., 2005). Moreover, this ERP component has also been associated with the storage of word representations in episodic memory (Rodríguez-Fornells et al., 2009; Wagner et al., 1998), the construction of lexical-semantic representations (Borovsky et al., 2010; Kutas and Federmeier, 2011) as well as with short-term and working memory functions (Hagoort, 2014; Kutas and Federmeier, 2011). Although the N200 and the LPC components have not gained the same linguistic attention as the N400, both metrics have been shown to be crucially involved in memory and learning (Bakker et al., 2015; Borovsky et al., 2010; Dittinger et al., 2016; Dittinger et al., 2017). In fact, the LPC is particularly susceptible to explicit memory processes such as episodic memory (Rugg and Curran, 2007), word recognition (Borovsky et al., 2012) and semantic access (Bakker et al., 2015; Hoshino and Thierry, 2012; Juottonen et al., 1996; Rohaut et al., 2015). Otherwise, the N200 component has been linked to early lexical selection, initial word-form recognition (van den Brink et al., 2001) as well as to phonological processes (Connolly and Phillips, 1994; Friedrich and Friederich, 2008).

While in the past the idea that anticipatory cognitive processes play a fundamental role in language has been contentious (DeLong et al., 2005), currently there is growing evidence at the electrophysiological level pointing to prediction-related pre-activation of lexical items at both the word- (Dikker and Pyllkanen, 2013; Roll et al., 2017; Soderstrom et al., 2016) and sentence-level (DeLong et al., 2005; Leon-Cabrera et al., 2019; Leon-Cabrera et al., 2017). For example, Van Petten and colleagues (Van Petten, 2014) showed that the N400 amplitude is related to the strength of the associations between two words as determined from corpus-based measures of word co-occurrence, with largest N400 responses when the target is not predictable from the preceding word (i.e., weak associations or unrelated words). More recently, initial word fragments with fewer lexical competitors have also been shown to elicit a larger early pre-activation negativity (~150–350 ms) compared to those with more competitors (Soderstrom et al., 2016). Furthermore, the amplitude of this ERP component was inversely correlated with the number of possible competitors, suggesting a gradual word pre-activation effect that was modulated as a function of prediction likelihood (Soderstrom et al., 2016). Notably, a similar sensitivity of ERP indices to linguistic predictions has also been demonstrated at the

sentence-level, at least for the N400 component. In fact, many studies' findings documented that the amplitude of the N400 component was modulated by the degree of contextual constraint, with smaller N400 amplitudes in response to expected compared to unexpected articles (DeLong et al., 2005) or nouns (DeLong et al., 2005; Leon-Cabrera et al., 2019; Leon-Cabrera et al., 2017). Drawing on this background, experiments in the auditory modality revealed that semantic integration during speech comprehension can begin even before word identification is complete (Van Petten et al., 1999). Moreover, by comparing familiar (proverbs) and unfamiliar sentences with congruous and incongruous endings (2 × 2 design), Cermolacce and colleagues (Cermolacce et al., 2014) demonstrated that the N400 effect (i.e., the difference between incongruous and congruous words) started about 200 ms earlier for proverbs where final words were strongly predictable from the sentence context. However, as pointed out by Pulvermuller and Grisoni (Pulvermuller and Grisoni, 2020), one problem in these studies is that ERPs in response to the target are possibly contaminated by cognitive processes other than prediction, such as attention, arousal or lexical-semantic integration. Accordingly, to properly track the neural basis of predictive linguistic processes, it is reasonable to examine brain activity before the target stimulus is presented. Hence, rather than analyzing ERPs to the target stimulus, we compared ERPs between pictures that enabled or did not enable to predict the upcoming words.

In this EEG study, we examined evidence for the neural coding of word pre-activation while participants learned the meaning of novel auditorily presented words through the repeated presentation of picture-word associations (learning condition). In this context, we deliberately used real existing Thai words to simulate foreign language learning, and the same stimuli have already been adopted in previous experiments of our group to assess the influence of musical expertise on phonetic-based word learning (Dittinger et al., 2016; Dittinger et al., 2017; Dittinger et al., 2019). Importantly, the task also included a control condition (non-learning condition) consisting of words that were randomly associated with different pictures so that participants could not make consistent or accurate predictions of the forthcoming words. With this purpose in mind, we analyzed mean ERP amplitudes during the learning process in responses to pictures preceding words in time windows corresponding to the visual N200, N400 and LPC components. Specifically, to control for stimulus-specific differences between the learning and the non-learning conditions, for each participant we computed difference waves (DW) by subtracting the ERPs of the first block from those of the second block, and compared EEG metrics between the two conditions. Given that only in the learning condition accurate predictions can develop over time, any electrophysiological difference (amplitude or topographic distribution) between the two conditions is taken to reflect condition-specific processes that are reducible, among other functions, to prediction-related pre-activation effects. However, this requirement alone is not necessarily sufficient to validate EEG metrics of word pre-activation. Hence, we used a more conservative criterion, and postulated that if specific EEG metrics are indeed sensitive indices of memory-based predictions, then ERP changes should also correlate with word learning performance. Based on previous EEG studies on language-related predictions, we expected that word pre-activation effects should be reflected by reduced N400 (DeLong et al., 2005; Leon-Cabrera et al., 2019; Leon-Cabrera et al., 2017) and increased LPC amplitudes (Freunberger and Roehm, 2016; Van Petten and Luka, 2012) across the two blocks of the learning condition. Otherwise, since the intrinsic meaning of the N200 component during word pre-activation has not yet been comprehensively addressed, for this ERP we did not have a clear a priori hypothesis, and hence we followed a rather explorative approach.

2. Materials & methods

The experimental design of this study was the same as the one we previously used for evaluating auditory ERPs during word learning through picture-word associations (Elmer et al., 2021). However, the

main difference between the two studies is that in the previous work we evaluated ERPs in response to words during learning, whereas in the current study we analyzed electrophysiological responses to pictures preceding words to track neural indices of word pre-activation. Since in both studies we used the same materials and methods, some paragraphs and sentences were literally reiterated from the description of the previous study.

2.1. Participants

Forty participants in the age range of 20–40 years (mean age = 25.46 years, SD = 4.9) and without neurological or psychological deficits were recruited for the study. Due to extensive EEG artifacts, one participant had to be excluded from data analyses. All participants were consistently right-handed (Annett, 1970), native German speakers and none of them grew up as a bilingual. However, since the participants were tested in Switzerland, which is a multilingual country, they spoke more than one language fluently. Furthermore, playing a musical instrument was not an exclusion criterion for the study. The participants were paid for participation and gave informed written consent in accordance with the procedures of the local ethics committee and the declaration of Helsinki.

2.2. Cognitive capability and pure tone audiometry

General intelligence was screened to ensure that all participants had an IQ in the average range, and was estimated using a standardized form of the KAI test [*Kurztest für Allgemeine Basisgrößen der Informationsverarbeitung*, (Lehrl et al., 1992)]. This procedure consisted of reading aloud meaningless sequences of 20 letters as quickly as possible, and of repeating auditory-presented letters and digits increasing in length (up to nine items). The KAI test has been shown to correlate about $r = 0.7$ with global IQ in healthy adults (Lehrl et al., 1992). All participants also underwent pure-tone audiometry (MAICO Diagnostic GmbH, Berlin) in the frequency range of 250–8000 Hz (MAICO Diagnostic GmbH, Berlin). According to this procedure, all participants demonstrated an unremarkable audiological status in that the tested frequencies could be heard below a threshold of 30 dB.

2.3. Auditory stimuli

The Thai syllables that served as words in the associative word learning task were taken from a corpus of twelve units (/ba0/, /ba:0/, /ba:1/, /ba1/, /pa0/, /pa:0/, /pa:1/, /pa1/, /p^ha0/, /p^ha1/, /p^ha:0/ and /p^ha:1/) previously created by Dittinger and colleagues (Dittinger et al., 2016). In order to reproduce natural speech variability, four versions of each syllable were recorded by a native female Thai speaker. Sound pressure level was normalized across all items to a mean level of 70 dB using the Praat software (<http://www.fon.hum.uva.nl/praat/>).

The auditory stimuli consisted of natural Thai monosyllabic words with short (/ba1/, /pa1/ and /p^ha1/; 261 ms on average) and long vowel duration (/ba:1/, /pa:1/, /p^ha:1/, /ba:0/, /pa:0/ and /p^ha:0/; 531 ms on average), with low-tone (/ba1/, /pa1/, /p^ha1/, /ba:1/, /pa:1/ and /p^ha:1/; F0 = 175 Hz on average) and mid-tone vowels (/ba:0/, /pa:0/ and /p^ha:0/; F0 = 218 Hz on average) as well as with vowels varying in voicing (/ba1/, /ba:1/ and /ba:0/, Voice Onset Time (VOT) = -144 ms versus /pa1/, /pa:1/ and /pa:0/, VOT = 3 ms) and in aspiration contrasts (/pa1/, /pa:1/ and /pa:0/, VOT = 3 ms versus /p^ha1/, /p^ha:1/ and /p^ha:0/, VOT = 77 ms).

Based on pilot experiments, this corpus of twelve words was reduced to ten to optimize the word learning curve. Furthermore, since aspirated syllables are part of the German phonological repertoire and are easy to distinguish for native German speakers, only two out of four of these stimuli were presented to each participant. However, to guarantee a certain degree of variability, we assigned the four aspirated words to two different pools of stimuli that consisted of the same eight words without

aspiration but differed in two aspirated items, namely /P^ha1/ and /P^ha0/ vs. /P^ha:1/ and /P^ha:0/. These two pools of ten stimuli were pseudo-randomly counterbalanced across participants. Furthermore, to exclude the influence of stimulus material on word learning, the words used in the learning and non-learning conditions were counterbalanced across participants. In particular, the words that in one version were consistently associated with the same pictures, in the other version were presented with inconsistent ones across participants. Accordingly, for each of the two pools of stimuli we created two different versions (pool 1 version 1: /ba1/, /ba:0/, /pa1/, /pa:0/, /p^ha:1/; pool 1 version 2: /ba:1/, /ba0/, /pa:1/, /pa0/, /p^ha:0/; pool 2 version 1: /ba1/, /ba:0/, /pa1/, /pa:0/, /p^ha0/; pool 2 version 2: /ba:1/, /ba0/, /pa:1/, /pa0/, /p^ha1/).

2.4. Visual stimuli

In the present work, we focused on word pre-activation effects, and analyzed visual ERPs in response to the pictures preceding the words. With this purpose in mind, for each of the twelve words used in the word learning experiment, we selected ten similar variations of black and white pictures (e.g., ten pictures of dogs). These pictures represented concrete living and non-living objects with a high prototypicality for the following semantic categories: fruits (apple), animals (dog), weapons (pistol), office supplies (pencil), body parts (arm), clothes (trousers), vehicles (car), tools (hammer), buildings (house), kitchen equipment (fork), musical instruments (tambourine) and furniture (table). These different pictures were chosen from the web based on previous studies that evaluated objects' prototypicality of different semantic categories (Barbarotto et al., 2002; Maess et al., 2002). All black-and-white pictures were matched in size (pixel width = 600; pixel height = 750) and presented in the middle of a computer screen.

As mentioned above, the words used in the learning and non-learning conditions were counterbalanced across participants to exclude the influence of auditory stimulus material on word learning. In contrast, as a side effect of this experimental procedure that was originally planned for evaluating auditory ERPs in response to words, the pictures were not counterbalanced across conditions. In particular, the words of the learning condition were consistently associated with pictures of the semantic categories of fruits (apple), weapons (pistol), body parts (arm), vehicles (car) and kitchen equipment (fork); aspirated item of pool 1) or furniture (table; aspirated item of pool 2). Otherwise, the words of the non-learning conditions were always presented with pictures of the semantic categories of animals (dog), office supplies (pencil), clothes (trousers), tools (hammer), and musical instruments (tambourine; aspirated item of pool 1) or buildings (house; aspirated item of pool 2). Even though the pictures used in the learning and non-learning conditions were different, according to the Leipzig corpora (shorturl.at/szNW4) they had similar word frequency (mean German word frequency of the pictures: learning condition = 10.66; non-learning condition = 11).

2.5. Experimental procedure

During the experimental session, the participants were seated within a Faraday cage in a comfortable chair at about one meter from a computer screen. Auditory stimuli were presented through HiFi headphones (HD590, Sennheiser Electronic GmbH, Wedemark, Germany) at about 70-dB sound pressure level. Visual and auditory stimuli presentation as well as the collection of behavioral responses was controlled by the Presentation software (Version 11.0, Neurobehavioral Systems, Berkeley CA).

2.6. Word learning task

The word learning task consisted of two successive blocks of 4.15 min each, and the participants were explicitly instructed to learn the meaning of the novel words based on picture-word associations (Fig. 1).

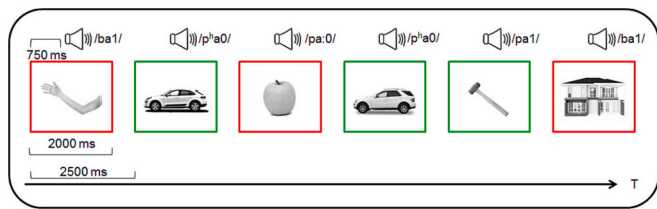


Fig. 1. Experimental design of the word learning task including trials of the learning (green) and non-learning (red) conditions. In the learning condition pictures of the same category (e.g., cars or hammers) were consistently associated with the same words, whereas in the non-learning condition pictures and words were inconsistently associated, and learning was not possible. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

In each block, half of the words of each pool (five) were consistently associated (learning condition) with variations of the same pictures (e.g., different pictures of a fork), whereas the other half was randomly coupled with different visual items (non-learning condition). Participants were not informed about the presence of a non-learning condition.

During the task, participants were exposed to one of the ten pictures that were presented for 2000 ms and followed, 750 ms after picture presentation onset (SOA), by one of the words (trial duration = 2500 ms). Each of the two blocks consisted of 100 trials, and every single word of the learning (5 words) and non-learning (5 words) condition was presented 10 times in association with 10 variations of the same pictures (learning condition) or two variations of each of the five inconsistent pictures (non-learning condition).

Immediately after the learning phase, performance was tested using a forced-choice (FC) task. In the FC task, four pictures, namely two of the learning and two of the non-learning condition, were simultaneously presented side by side on the screen for 6500 ms (trial duration). Words were presented 750 ms after the onset of the pictures, and the participants had to select the picture that matched the meaning of the learned word by pressing a corresponding response button. Furthermore, the participants were instructed to press an additional response key if they thought that they had not learned the meaning of the presented word. This additional response key served as correct response for the words of the non-learning condition. The test phase consisted of 30 trials, each of the 5 words of the learning and non-learning condition was presented 3 times, and each picture (including its variations) was presented 12 times. The test phase had a duration of 3.25 min.

2.7. EEG data acquisition and pre-processing

The EEG was recorded during the word learning task but not during the FC task at a sampling rate of 1000 Hz with a high-pass filter of 0.1 Hz using an EEG amplifier (Brainproducts, Munich, Germany). Thirty-two active Ag/Cl electrodes were located at standard positions according to the international 10/20 system, the reference electrode was placed on the tip of the nose, and electrode impedance was kept below 10 k Ω . The EEG data were pre-processed using the Brain Vision Analyzer software (Version 2.1.0; Brain Products, GmbH). In particular, the data were re-referenced offline to the averaged left and right mastoids, and filtered with a bandpass filter of 0.1–30 Hz (slope of 48 dB/oct) and a Notch filter of 50 Hz. Furthermore, an independent component analysis (ICA) was used to identify and correct vertical and horizontal ocular movements, and the remaining artifacts were automatically removed according to a maximum-minimum criterion of 100 μ V.

For each participant, condition and block, single epochs time-locked to the onset of the pictures were extracted in the time window from –200 to 750 ms, averaged and baseline-corrected. Furthermore, to isolate neural indices of word pre-activation while controlling for the different visual stimuli used in the two conditions, for each participant and condition (learning and non-learning) we computed DWs by

subtracting the ERPs of the first block from the EEG traces of the second block. Accordingly, the comparison of the DWs between the two conditions precludes that any observed differences between the learning and non-learning conditions can be due to item specific differences or differences in semantic category. Individual averages and DWs were then used to compute grand averages for the whole sample of participants.

2.8. EEG analyses

Given that prediction can only develop in the course of the learning condition, and in order to correct for the different pictures used in the learning and non-learning conditions, we examined neural markers of word pre-activation by comparing the DWs (block 2 minus block 1) between the two conditions. In this context, we focused on time windows overlapping with the N200 (200–350 ms), N400 (350–550 ms) and LPC (550–750 ms) components, and for each participant and condition we extracted mean DW amplitudes in three regions of interest (ROI) located at anterior (average of F3, Fz, F4), central (average of C3, Cz, C4) and posterior (average of P3, Pz, P4) scalp sites. The time windows used for analyses were selected according to the grand average waveforms (Fig. 2), whereas the ROIs were chosen based on the topographic maps (Fig. 3) as well as on previous literature on word learning showing learning-related effects along the anterior-posterior topographical axis (Dittinger et al., 2016; Elmer et al., 2021).

2.9. Statistical analyses

All analyses were performed using **parametric statistics** implemented in the IBM SPSS Statistics 22 software package (SPSS, an IBM company, Armonk, New York, USA). The percentages of correct responses to words of the learning and non-learning conditions as well as RTs were evaluated using *t*-tests for dependent samples. Otherwise, mean DW amplitudes of the visual evoked N200, N400 and LPC components were examined using separate ANOVAs (repeated measurements) with the within-subject factors of condition (learning vs. non-learning) and ROI (anterior vs. central vs. posterior). Significant main effects and interactions were further inspected using post-hoc *t*-tests or ANOVAs (Bonferroni-corrected for multiple comparisons). Finally, correlative analyses (Pearson's *r*, two-tailed) were used to carve out relationships between neural indices of word pre-activation and word learning performance.

3. Results

3.1. Behavioral data

The behavioral data of the FC task (percentage of correct responses and RTs to words of the learning and non-learning conditions) were analyzed using *t*-tests for dependent samples. The analysis of the percentage of correct responses revealed that the participants made more correct responses ($t_{(38)} = 5.371$, $p < .001$, Cohen's $d = 0.86$) and demonstrated shorter RTs ($t_{(38)} = -5.679$, $p < .001$, Cohen's $d = 0.909$) in response to the words of the learning compared to those of the non-learning condition (Fig. 4). Furthermore, both the percentage of correct responses of the learning ($t_{(38)} = 13.315$, $p < .001$) and non-learning ($t_{(38)} = 2.961$, $p = .005$) conditions were above chance level (20 %). Accordingly, based on the consistent mapping procedure used in the learning condition, the participants were able to learn the new words, but they were also aware that the meaning of some words could not be acquired. Nonetheless, the better performance in the learning compared to the non-learning condition could possibly also have been influenced by the fact that the participants were not informed about the presence of a non-learning control condition, or even by a bias of the participants to believe that a word has to correspond to a picture.

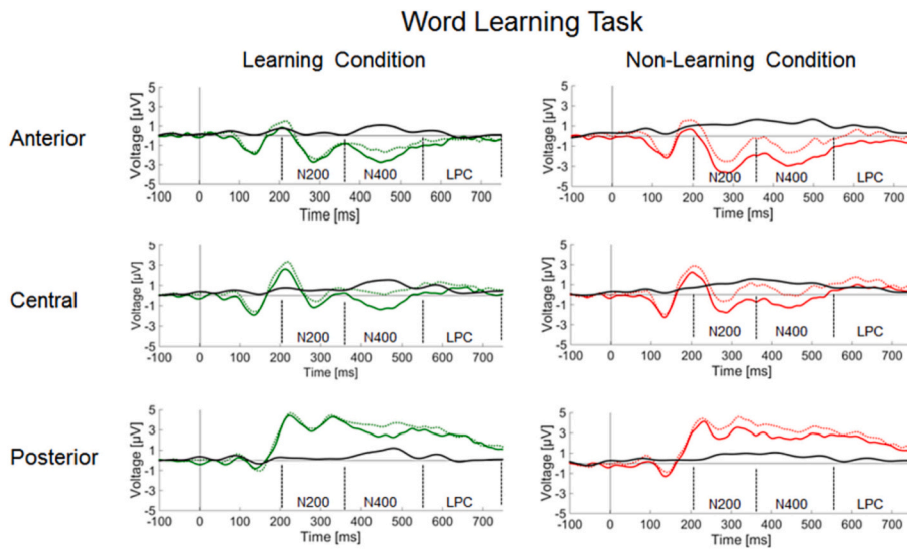


Fig. 2. The grand-averages at anterior, central and posterior regions-of-interest (ROI) are shown separately for the learning (left side) and non-learning (right side) conditions. The solid green and red lines depict the event-related potentials (ERPs) of the first block, whereas the dashed colored lines refer to the ERPs of the second block. In both conditions, the black lines correspond to the difference wave (DW) between the two blocks (2nd - 1st block). For illustrative purposes, the DWs have been filtered using a low-pass filter of 12 Hz. The y-axis depicts amplitudes in μV , whereas the x-axis reflects time in ms. Negativity is plotted down. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

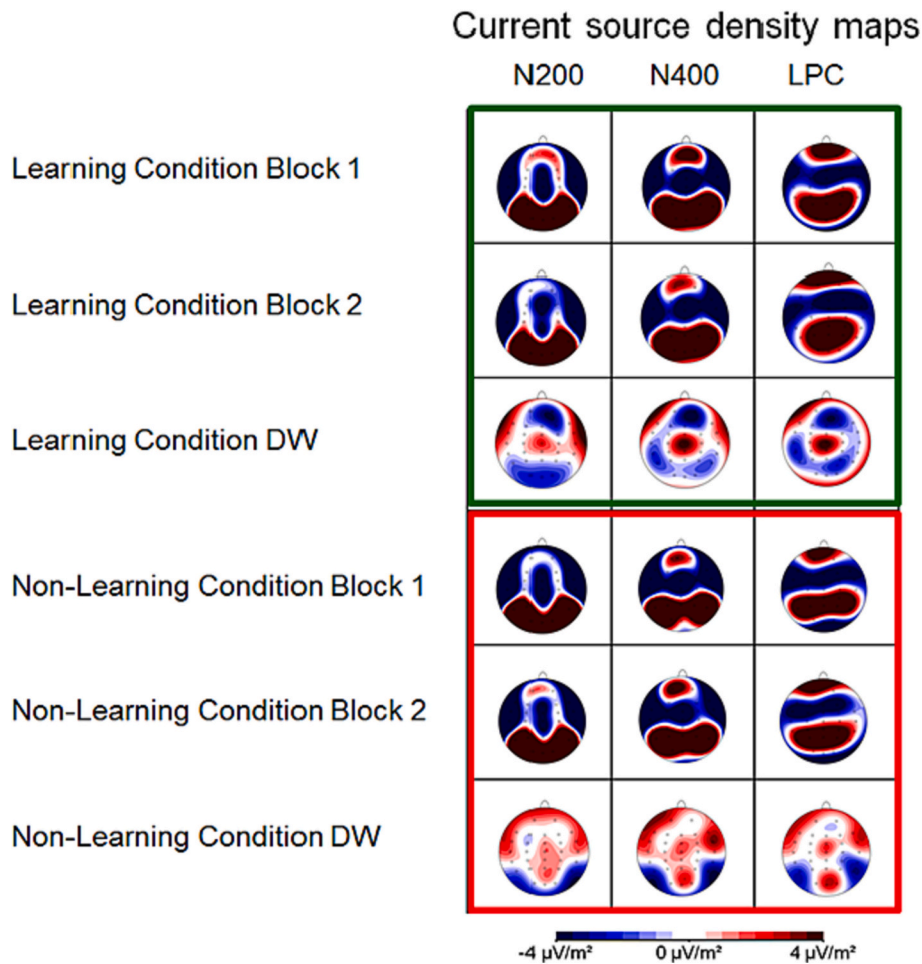


Fig. 3. The current source density maps are shown for each condition (green box = learning condition, red box = non-learning condition), the first block (first row), the second block (second row) and the DWs (third row). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.2. Electrophysiological data and brain-behavior relationships

N200 time window.

Mean N200 DW amplitudes were compared between the two

conditions and the three ROIs using a 2×3 ANOVA. This procedure yielded a main effect of condition ($F_{(1, 38)} = 5.406, p = .026$; partial $\eta^2 = 0.125$) that was associated with a larger, but topographic unspecific, reduction of N200 amplitudes from block 1 to block 2 in the non-

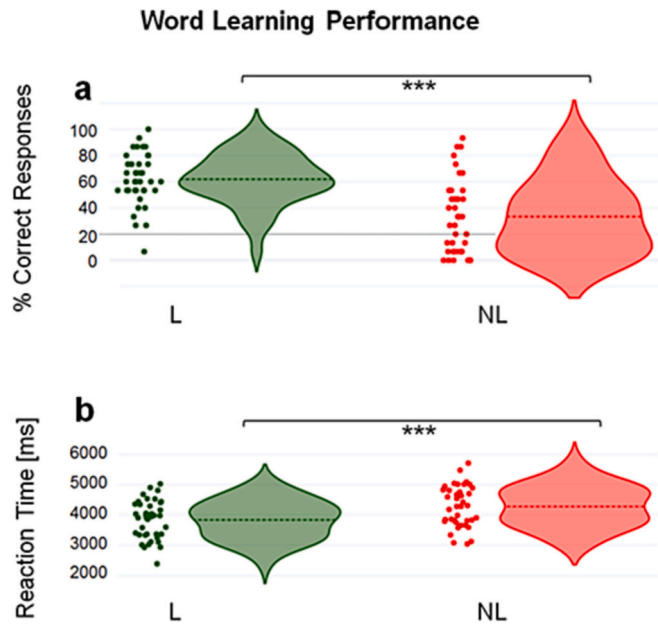


Fig. 4. Single-subject data and violin plots with density distribution and mean. The percentage of correct responses (a) and reaction times (b) are shown for the words of the learning (L, green) and the non-learning (NL, red) conditions. The dashed line in panel (a) depicts chance level (20 %). *** = $p < .001$. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

learning compared to the learning condition (Figs. 2 and 5). Otherwise, the main effect of ROI ($F_{(1.162, 44.173)} = 3.505, p = .062$; partial $\eta^2 = 0.084$) as well as the condition \times ROI interaction ($F_{(1.272, 48.345)} = 1.051, p = .328$; partial $\eta^2 = 0.027$) failed to reach significance. Since the stronger neural change in the non-learning condition was unlikely to reflect word pre-activation effects, we refrained from computing additional correlative analyses.

3.3. N400 time window

The 2×3 ANOVA (2 conditions and 3 ROIs) yielded a quadratic condition \times ROI interaction ($F_{(1, 38)} = 5.206, p = .028$; partial $\eta^2 = 0.12$), whereas the main effects of condition ($F_{(1, 38)} = 0.866, p = .358$; partial $\eta^2 = 0.022$) and ROI ($F_{(1.153, 43.804)} = 3.114, p = .079$; partial $\eta^2 = 0.076$) did not reach significance. Separate univariate ANOVAs for the two conditions revealed that the quadratic interaction originated from the learning condition ($F_{(1, 38)} = 23.351, p < .001$, see Fig. 5), and additional t -tests for dependent samples (Bonferroni-corrected p value for 3 comparisons = .016) showed that in the learning condition there was a larger N400 reduction from block 1 to block 2 at the central compared to the anterior ROI ($t_{(38)} = -2.802, p = .008$). Since mean N400 amplitudes did not differ between the two conditions (Bonferroni-corrected p value for 3 comparisons = .016; anterior: $t_{(38)} = -1.783, p = .083$, Cohen's $d = 0.348$; central: $t_{(38)} = -0.369, p = .714$, Cohen's $d = 0.074$; posterior: $t_{(38)} = -0.338, p = .737$, Cohen's $d = 0.067$), the results highlight distinct topographies that were not accompanied by differences in magnitude.

Based on these condition-specific results with a clear topographic sharpness, we performed additional correlative analyses and predicted a positive relationship between mean N400 DW amplitudes at the central ROI and word learning performance. This analysis revealed a positive correlation between mean N400 DW amplitudes at the central ROI and the percentage of correct responses to words of the learning condition ($r = 0.355, p = .027$, Fig. 6). In particular, a larger reduction of N400 amplitudes from the first to the second block was associated with better word learning performance. Finally, as an additional control and to

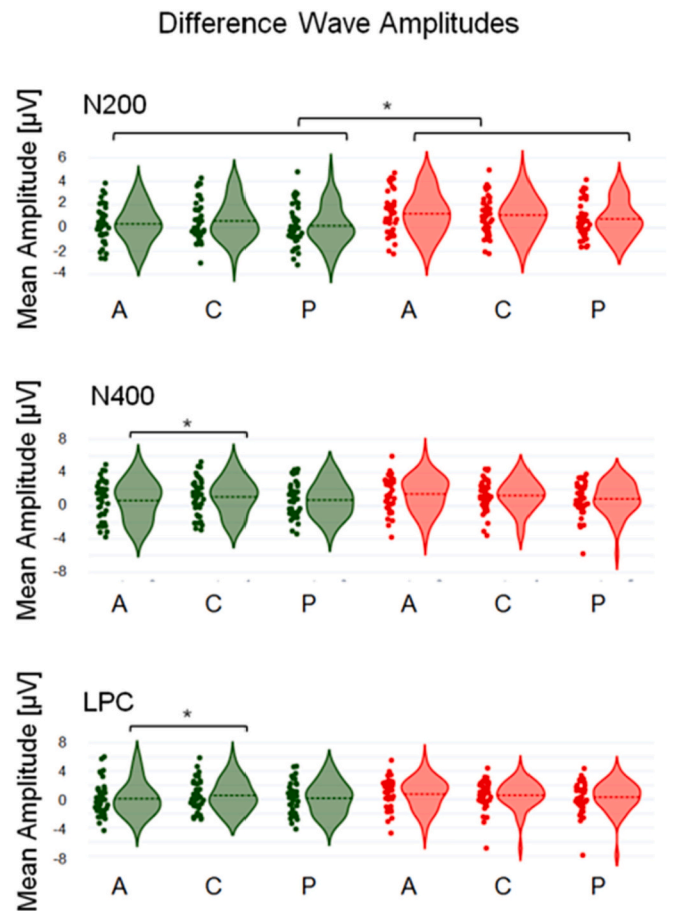


Fig. 5. Single-subject data and violin plots with density distribution and mean. Mean difference wave (DW) amplitudes are shown separately for the N200 (first row), N400 (second row) and LPC (third row) time windows, the two conditions (learning = green, non-learning = red) and the three regions-of-interest (A = anterior, C = central, P = posterior). * = $p < .05$. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

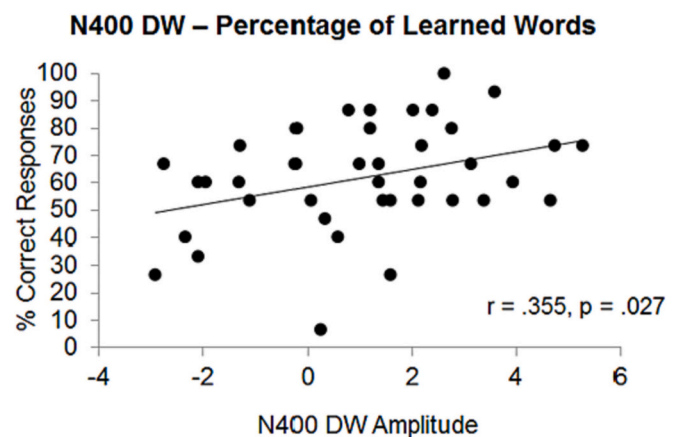


Fig. 6. Significant correlation (two-tailed) between mean N400 difference wave (DW) amplitudes at central electrodes and the percentage of correct responses to words of the learning condition.

provide further evidence for the specificity of the brain-behavior relationship we found in the learning condition, we also correlated the same behavioral index with mean N400 DW amplitudes at the central ROI of the non-learning condition. However, this correlation did not reach

significance ($r = 0.088$, $p = .594$).

3.4. LPC time window

The analysis of mean LPC DW amplitudes by means of a 2×3 ANOVA (2 conditions and 3 ROIs) yielded a quadratic condition \times ROI interaction ($F_{(1, 38)} = 4.867$, $p = .033$; partial $\eta^2 = 0.114$). In contrast, the main effects of condition ($F_{(1, 38)} = 0.499$, $p = .484$; partial $\eta^2 = 0.013$) and ROI ($F_{(1.151, 43.730)} = 1.262$, $p = .274$; partial $\eta^2 = 0.032$) did not reach significance. Separate univariate ANOVAs for the two conditions showed that the quadratic interaction originated from the learning condition ($F_{(1, 38)} = 17.711$, $p < .001$). Post-hoc t -tests for dependent samples (Bonferroni-corrected p value for 3 comparisons = .016) revealed that in the learning condition the LPC increased more strongly from block 1 to block 2 at the central compared to the anterior ROI ($t_{(38)} = -2.588$, $p = .014$). Otherwise, we did not reveal LPC magnitude differences between the learning and non-learning conditions (Bonferroni-corrected p value for 3 comparisons = .016; anterior: $t_{(38)} = -1.411$, $p = .166$, Cohen's $d = 0.284$; central: $t_{(38)} = -0.058$, $p = .954$, Cohen's $d = 0.011$; posterior: $t_{(38)} = -0.356$, $p = .724$, Cohen's $d = 0.071$). Based on the condition-specific results, we additionally correlated mean LPC DW amplitudes at the central ROI with word learning performance. However, the correlation did not reach significance ($r = 0.247$, $p = .13$). Also in the non-learning condition the same correlation failed to reach significance ($r = 0.17$, $p = .302$).

4. Discussion

4.1. General discussion

In the present EEG study, we thought to isolate neural indices of novel word pre-activation by comparing ERPs to pictures that preceded words between a learning condition with high prediction likelihood and a non-learning control condition with low prediction. Thereby, we focused on the N200, N400 and LPC components which have previously been shown to be sensitive to word learning (Bakker et al., 2015; Borovsky et al., 2010; Dittinger et al., 2016; Dittinger et al., 2019). To control for stimulus-specific differences between the two conditions, we computed DWs across the two blocks of the learning and non-learning conditions. This procedure is particularly fruitful in that the resulting DWs contain condition-specific information, including changes in word

pre-activation and possibly changes in other cognitive functions, like attention and cognitive load. Furthermore, we used different pictures of the same concept to avoid strong perceptual priming effects (Friedman and Cycowicz, 2006).

The comparison of the DWs between the learning and non-learning conditions revealed ERP effects that fulfilled the requirements for word pre-activation, especially in the time window corresponding to the N400 component. In fact, in the learning condition the N400 component most markedly decreased from block 1 to block 2 at central compared to anterior electrodes, whereas in the non-learning condition we generally observed widespread effects in the N200, N400 and LPC time windows without any topographical specificity along the anterior-posterior axis. Remarkably, the dynamic N400 changes we revealed as a function of word learning were also predictive of word learning performance.

4.2. N200 time window

The evaluation of the DWs corresponding to the N200 time window yielded a topographically-unspecific effect that emerged from larger N200 amplitude reductions from block 1 to block 2 in the non-learning compared to the learning condition. Furthermore, from Fig. 7, one can see that when both block 1 and block 2 are divided in two sub-blocks, N200 amplitudes decreased from the first to the second half of block 1 as well as from the first to the second half of block 2. Given that genuine predictions can only develop in the learning condition, it is unlikely that the N200 effect we revealed in the non-learning condition reflected word pre-activation. Hence, we might speculate that the more pronounced N200 changes we revealed in the non-learning condition originated from cognitive processes other than prediction. Drawing on this background, the N200 results are interpreted as suggesting that the non-learning condition placed differential demands on attentional, short-term memory or working memory resources compared to the learning condition. Such an interpretation is strengthened, for example, by previous findings showing that N200 amplitudes are sensitive to attentional control, and increase in parallel with attentional load (Behzadnia et al., 2018; Ruz and Nobre, 2008). Furthermore, the topographically-unspecific N200 modulation we revealed across the blocks of the non-learning condition could also reflect a reduced selection negativity (SN) effect, which has previously been reported for attended compared to non-attended objects (Molholm et al., 2007; Talsma et al., 2007). Accordingly, the reduced N200 amplitudes we

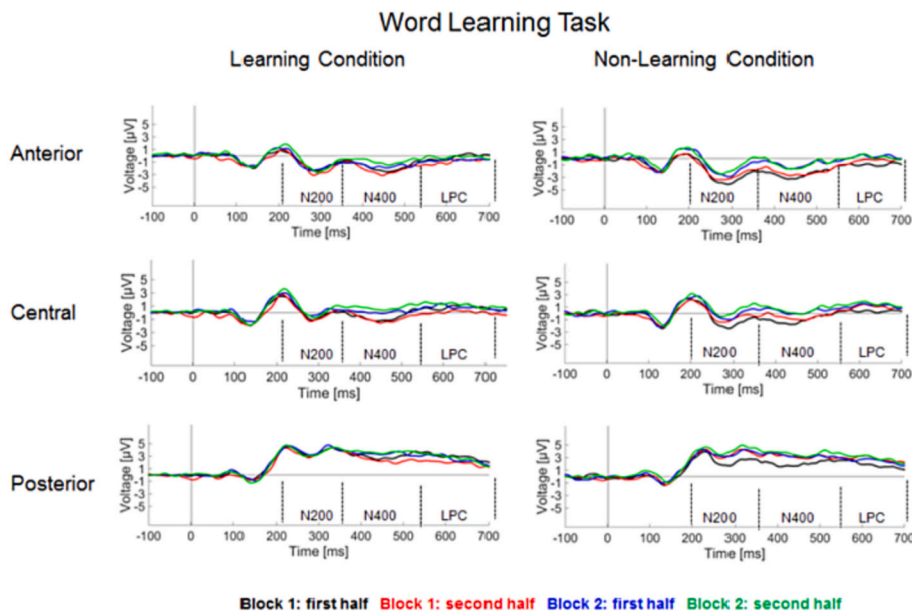


Fig. 7. The grand-averages at anterior, central and posterior regions-of-interest (ROIs) are shown separately for the learning (left side) and the non-learning (right side) conditions as well as for the first half of block 1 (black), the second half of block 1 (red), the first half of block 2 (blue), and the second half of block 2 (green). The y-axis depicts amplitudes in μV , whereas the x-axis reflects time in ms. Negativity is plotted down. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

noticed in the second compared to the first block of the non-learning condition could principally indicate that in the course of the experiment the participants recognized that they did not learn the associations between pictures and words, and hence focused less attention on the pictures that were not consistently associated with the same words. A second interpretation is that the reduction of the N200 component in block 2 compared to block 1 of the non-learning condition was related to a lower recruitment of short-term or working memory resources, possibly because controlled search of picture-related words was not possible, and therefore diminished over time. Such a perspective would also be in line with previous studies that reported a parametric modulation of N200 amplitudes as a function of memory load (Missonnier et al., 2003; Morgan et al., 2010).

4.3. N400 time window

Nowadays, it is generally acknowledged that N400 amplitudes are inversely related to the expectancy of a given word (DeLong et al., 2005; Leon-Cabrera et al., 2019; Leon-Cabrera et al., 2017) as well as to the ease of accessing information from lexical-semantic (Kutas and Federmeier, 2011) and episodic memory (Rodríguez-Fornells et al., 2009; Wagner et al., 1998). Currently, there is also compelling evidence that semantic memory-related N400 manifestations are usually particularly pronounced at central and posterior electrodes (Kutas and Federmeier, 2011), and that during word learning this ERP component demonstrates a spatial displacement along the anterior-posterior topographical axis (Bakker-Marshall et al., 2018; Borovsky et al., 2012; Dittinger et al., 2016; Dittinger et al., 2017; Dittinger et al., 2019; Elmer et al., 2021). In line with these previous studies on word learning, we revealed the largest N400 changes across the two blocks of the learning condition at central compared to anterior electrodes, whereas in the non-learning condition N400 modulations were spatially widespread without any topographical sharpness (Fig. 5). Since the N400 changes in the non-learning condition were topographically and temporally unspecific and prediction was not possible, the diffuse effects were possibly related to reduced top-down control of mnemonic processes or attention-related modulations (Kiefer, 2008).

Although the widespread N400 reduction across the two blocks of the non-learning condition was somewhat unexpected, we may speculate that this effect was mediated by a reduced allocation of attentional resources to the pictures that could not be associated with a specific word over time. Such an interpretation can be deduced from previous studies showing an inverse relationship between N400 amplitudes and attentional engagement (Deacon and Shelley-Tremblay, 2000; Holcomb, 1988; Okita and Jibu, 1998), and would also make sense in light of the finding that attention during semantic encoding facilitates the binding of events to the context in which they occurred (Cowan, 1995; Okita and Jibu, 1998; Otten, 1996). Since in the non-learning condition the binding between pictures and words was not possible, the participants possibly focused less attention on the figural representations, resulting in a general depression of the N400 component along the entire anterior-posterior topographical axis. A second interpretation is that the reduced N400 amplitudes in the non-learning condition might have been driven by less controlled stimulus processing. In this context, it is conceivable that in the non-learning condition the participants were aware that picture-word associations could not be learned, and hence they reduced the memory encoding effort. Furthermore, as a third interpretation, we cannot exclude the possibility that the N400 effect we observed in the non-learning condition was related to a differential encoding or retrieval of the pictures. In particular, since in the non-learning condition the pictures were not consistently associated with specific words, the figural objects of the non-learning condition were possibly more difficult to process because they were associated with less information compared to those of the learning condition, and hence they were differently encoded over the time course of the experiment. Such a perspective would be in line with previous studies focusing on semantic congruency effects, and

showing that information which is congruent with prior knowledge or existing schemes is often processed more efficiently and remembered better than incongruent information (Bein et al., 2015; Packard et al., 2017; Staresina et al., 2009; van Kesteren et al., 2014). Anyhow, further studies using constant and variable picture-word mapping procedures are needed to better understand the exact meaning of the widespread N400 effect we revealed over time in the non-learning condition.

The N400 changes we revealed at central electrodes in the learning condition (Figs. 3 and 5) are in line with previous literature on word learning in adults (Borovsky et al., 2012; Mestres-Misse et al., 2007) and children (Friedrich and Friederici, 2008). However, as expected, the N400 modulation across the two blocks of the learning condition was in the opposite direction than the one classically reported in previous studies on word learning which evaluated the ERPs in response to auditory words. In fact, in the learning condition we revealed a reduction of N400 amplitudes from block 1 to block 2, whereas in classical word learning tasks N400 amplitudes typically increase across the blocks (Dittinger et al., 2016; Dittinger et al., 2017; Dittinger et al., 2019). In one of the first word learning EEG studies, McLaughlin and colleagues (McLaughlin et al., 2004) revealed a rapid increase in N400 amplitudes while the participants learned novel words in a second language. Similar EEG patterns were also observed when participants learned the meaning of rare words (Perfetti et al., 2005) or even novel words or pseudowords in the context of highly constrained sentences (Batterink and Neville, 2011; Borovsky et al., 2012; Borovsky et al., 2010; Mestres-Misse et al., 2007). However, there are fundamental differences between these previous word learning experiments and our word pre-activation paradigm. In fact, unlike previous studies on associative word learning that examined ERPs in response to words, in the present work we evaluated brain responses to pictures. Hence, increased N400 responses in response to words might reflect the cognitive demands placed on memory encoding, on the storage of information and on the building up of lexical-semantic representations (Borovsky et al., 2010; Kutas and Federmeier, 2011). In contrast, smaller N400 amplitudes while processing pictures might mirror reduced processing costs associated with lexical-semantic (Borovsky et al., 2010; DeLong et al., 2005; Kutas and Federmeier, 2011) or episodic memory retrieval as a function of associative learning (Rodríguez-Fornells et al., 2009; Wagner et al., 1998). Finally, it is noteworthy to mention that in the first block of the word learning task, the participants had to acquire the meaning of only five words, and each of them was repeated ten times. Thus, it is possible that N400 amplitudes first increased across trials in block 1 until the meaning was stabilized into semantic networks. However, since the same five words were presented again in block 2, word meaning was possibly overlearned and N400 amplitude started to decrease, as typically found when words are repeated (Besson et al., 1992; Rugg, 1985). Such a perspective would be compatible with the ERPs of the learning condition (Fig. 7) obtained by arbitrarily dividing each block into two sub-blocks. In fact, N400 amplitudes tended to increase from the first to the second part of block 1, whereas in block 2 the same neural indices decreased over time. In contrast, in the non-learning condition N400 amplitudes steadily decreased from the first part of block 1 to the second part of block 2.

The reduction of the N400 component from block 1 to block 2 of the learning condition at central electrodes is in line with previous studies indicating that smaller amplitudes of this ERP component index repetition effects (Besson et al., 1992; Rugg, 1985), mnemonic facilitation (Kutas and Federmeier, 2011; Wagner et al., 1998) as well as linguistic predictions (DeLong et al., 2005; Lau et al., 2013; Mantegna et al., 2019). The latter perspective is further corroborated by the correlation analyses showing that the degree of N400 modulation was related to participants' word learning performance. This relationship is particularly noteworthy, and emphasizes that the N400 component is sensitive enough to measure the pre-activation or retrieval of phonological word forms corresponding to the pictures. Nevertheless, our data are not conclusive on which kind of representations are pre-activated. In fact,

based on linguistic frameworks of language production stages (Dell and O'Seaghdha, 1992; Levelt et al., 1991), pre-activation is thought to be related to lexical word access, where semantic features of the pictures activate lemmas or abstract lexical word forms. However, novel words can also be retrieved based on phonological information alone without the need to recruit lexical-semantic knowledge. In this context, it is important to mention that the advantage of the present word-learning paradigm is that we used different but conceptually related pictures which were constantly mapped onto the same novel words. Such a variable picture-word mapping procedure might facilitate the encoding of novel words at the lexical-semantic level, whereas constant mapping tasks can be solved using episodic or associative memory functions without the need to access lexical-semantic knowledge. Based on this reasoning, the reduced N400 amplitudes we observed in the second compared to the first block of the learning condition might reflect, to a certain degree, a more efficient access to the novel words from lexical-semantic memory. Anyhow, further studies using constant and variable picture-word mapping procedures are needed to better understand what type of representations are accessed during short-term word learning.

Finally, it is important to note that the N400 effects we revealed demonstrated a more anterior topographical distribution than the one classically observed in semantic language processing tasks (Kutas and Federmeier, 2011). Nevertheless, such a topographical distribution is in line with previous EEG studies showing that when novel words which have been learned from a sentence context are used as primes of real existing words, semantic priming effects are reflected by a fronto-central N400 distribution (Elgort et al., 2015; Mestres-Misse et al., 2007). Similar fronto-central N400 effects (FN400) have also been associated with conceptual priming in both memory and familiarity-based recognition paradigms (Besson et al., 1992; Friedman, 1990; Paller and Kutas, 1992; Rugg, 1990; Rugg and Curran, 2007). Furthermore, Voss and Federmeier (Voss and Federmeier, 2011) revealed comparable FN400 distributions in a semantic priming condition and a familiarity-based recognition task, possibly indicating that the N400 components reported in the language (semantic priming) and in the memory literature (old/new effect) might reflect implicit conceptual priming effects that occur when two related words are presented close in time or a particular word is repeated after a certain delay.

4.4. LPC time window

Interestingly, the LPC results as well as the topographies of the DWs were remarkably similar to those of the N400 component. In fact, even though LPC amplitudes increased instead of decreasing across blocks, the most pronounced changes were limited to central electrodes. Increased positive ERP deflections have often been reported in the memory literature in the time range of 300–800 ms, with early effects (300–500 ms) usually attributed to familiarity-based recognition and later ones (400–800 ms) associated with memory recollection and remembering in general (Duzel et al., 1997; Wilding and Rugg, 1996). More recently, LPC amplitudes have also been shown to be related to working memory load (Gevins and Smith, 2000; Lefebvre et al., 2005). Furthermore, although the functional role of the LPC in predictive processes is not yet well understood, there is still evidence for associations between the LPC and predictive coding in different domains, including feedback expectations (Moris et al., 2013) and language processing (Freunberger and Roehm, 2016; Van Petten and Luka, 2012).

The topographic similarity between N400 and LPC responses in both the learning and non-learning conditions might lead to the conclusion that these ERPs reflected a common process, like for example, word repetition (Besson et al., 1992). Otherwise, it is also conceivable that the LPC was just a continuation of the N400 effect. Nevertheless, unlike the N400, the LPC changes we revealed across the two blocks of the learning condition were not predictive of word learning performance. Hence, we speculate that the increased LPC amplitudes we observed as a function of

word learning at central electrodes reflected domain-general cognitive functions, like verbal memory or memory load (Gevins and Smith, 2000; Lefebvre et al., 2005), which are necessary to keep the pre-activated words in short-term or working memory for later comparison with the auditory presented words.

5. Limitations

The present study has some methodological limitations that are worth mentioning. A first limitation is that learning performance was tested only once after the two learning blocks instead of assessing learning attainment separately for each block. This implies that we were not able to provide concrete empirical evidence showing that word learning increased from block 1 to block 2. Nevertheless, based on several previous studies of our group where we used exactly the same Thai words in association with a picture-word mapping procedure (Dittinger et al., 2016; Dittinger et al., 2019; Elmer et al., 2021), we know that N400 amplitudes in response to words dynamically increase across the first two blocks, which in our opinion is a strong argument for incremental learning over time. Such a perspective is also substantiated by several behavioral studies which used similar associative word learning tasks and demonstrated an increase in performance across learning blocks (Duyck et al., 2003; Freundlieb et al., 2012). A second shortcoming of the study is that the implementation of the experiment and the coding of the stimuli did not enable to evaluate single-word learning accuracy and word-specific ERPs. Such a procedure would be particularly fruitful for examining whether single-word learning performance would be a better predictor of word-specific ERP modulations than average word learning attainment. Hence, future studies should keep in mind this important aspect, and consider using learning accuracy as a continuous predictor to strengthen the interpretation of word pre-activation effects during associative word learning tasks.

6. Conclusions

Using a word learning paradigm that included an experimental condition with maximal prediction likelihood as well as a control condition with high prediction error, we provided evidence for the sensitivity of the N400 component to measure word pre-activation effects. In fact, this ERP component was not only specifically modulated at central electrodes as a function of learning, but N400 amplitudes also correlated with word learning performance. Although the LPC was not predictive of word learning, we may speculate that this ERP component possibly mirrored the neural process of keeping the pre-activated items in memory for later comparison. These results contribute to a better understanding of how predictive processes in response to pictures preceding words bolster word learning through the involvement of additional top-down mechanisms that cannot directly be inferred from classical word learning paradigms. Furthermore, we provided new insights on how the N400 component is differentially modulated during word learning as a function of encoding and retrieval processes. In fact, while during the meaning acquisition process increased N400 amplitudes over time are thought to reflect the encoding and consolidation of novel words at the lexical-semantic level, retrieval-based word pre-activation effects are associated with reduced N400 amplitudes. Certainly, future work is needed to better determine how encoding and retrieval processes interact during word learning, and to elucidate whether word learning performance can be optimized using tasks additionally requiring the active retrieval of words during learning.

CRedit authorship contribution statement

SE, MB, and ARF planned the study, and Julia Brocchetto performed the EEG measurements. SE analyzed the EEG data and performed the statistical analyses. SE, MB, and ARF contributed to the interpretation of the data and SE wrote the manuscript. MB and ARF contributed to the

writing and editing of the paper.

Declaration of competing interest

The authors declare no competing interests.

Data availability

The EEG data of this study are available from the first author upon reasonable request.

Acknowledgments

This research was supported by the Swiss National Science Foundation (SNF, grant no. 320030_163149 to Lutz Jäncke), the French National Agency for Research (ANR, program “Investissements d’Avenir”, ANR-11-IDEX-0001-02 to MB) and the Ministerio de Ciencia, Innovación y Universidades (PGC2018-099859-B-I00 to ARF).

References

- Annett, M., 1970. A classification of hand preference by association analysis. *Br. J. Psychol.* 61 (3), 303. <https://doi.org/10.1111/j.2044-8295.1970.tb01248.x>.
- Bakker, I., Takashima, A., van Hell, J.G., Janzen, G., McQueen, J.M., 2015. Tracking lexical consolidation with ERPs: lexical and semantic-priming effects on N400 and LPC responses to newly-learned words. *Neuropsychologia* 79, 33–41. <https://doi.org/10.1016/j.neuropsychologia.2015.10.020>.
- Bakker-Marshall, I., Takashima, A., Schoffelen, J.M., van Hell, J.G., Janzen, G., McQueen, J.M., 2018. Theta-band oscillations in the middle temporal gyrus reflect novel word consolidation. *J. Cogn. Neurosci.* 30 (5), 621–633. https://doi.org/10.1162/jocn_a.01240.
- Bar, M., 2009. The proactive brain: memory for predictions. *Philos.Trans.R.Soc.BBiol.Sci.* 364 (1521), 1235–1243. <https://doi.org/10.1098/rstb.2008.0310>.
- Barbarotto, R., Laiacona, M., Macchi, V., Capitani, E., 2002. Picture reality decision, semantic categories and gender. A new set of pictures, with norms and an experimental study. *Neuropsychologia* 40 (10), 1637–1653. [https://doi.org/10.1016/s0028-3932\(02\)00029-5](https://doi.org/10.1016/s0028-3932(02)00029-5).
- Batterink, L., Neville, H., 2011. Implicit and explicit mechanisms of word learning in a narrative context: an event-related potential study. *J. Cogn. Neurosci.* 23 (11), 3181–3196. https://doi.org/10.1162/jocn_a.00013.
- Behzadnia, A., Ghassemi, F., Chermahini, S.A., Tabanfar, Z., Taymourtash, A., 2018. The neural correlation of sustained attention in performing conjunctive continuous performance task: an event-related potential study. *Neuroreport* 29 (11), 954–961. <https://doi.org/10.1097/Wnr.0000000000001062>.
- Bein, O., Livneh, N., Reggev, N., Gilead, M., Goshen-Gottstein, Y., Maril, A., 2015. Delineating the effect of semantic congruency on episodic memory: the role of integration and relatedness. *Plos One* 10 (2), e0115624. <https://doi.org/10.1371/journal.pone.0115624>.
- Benitez, V.L., Saffran, J.R., 2018. Predictable events enhance word learning in toddlers. *Curr. Biol.* 28 (17), 2787–+. <https://doi.org/10.1016/j.cub.2018.06.017>.
- Besson, M., Kutas, M., Vanpetten, C., 1992. An event-related potential (ERP) analysis of semantic congruity and repetition effects in sentences. *J. Cogn. Neurosci.* 4 (2), 132–149. <https://doi.org/10.1162/jocn.1992.4.2.132>.
- Borovsky, A., Kutas, M., Elman, J., 2010. Learning to use words: event-related potentials index single-shot contextual word learning. *Cognition* 116 (2), 289–296. <https://doi.org/10.1016/j.cognition.2010.05.004>.
- Borovsky, A., Elman, J.L., Kutas, M., 2012. Once is enough: N400 indexes semantic integration of novel word meanings from a single exposure in context. *Lang. Learn. Dev.* 8 (3), 278–302. <https://doi.org/10.1080/15475441.2011.614893>.
- Brouwer, H., Fitz, H., Hoeks, J., 2012. Getting real about semantic illusions: rethinking the functional role of the P600 in language comprehension. *Brain Res.* 1446, 127–143. <https://doi.org/10.1016/j.brainres.2012.01.055>.
- Cermolacce, M., Scannella, S., Faugere, M., Vion-Dury, J., Besson, M., 2014. “All that glitters is not ... alone”. Congruity effects in highly and less predictable sentence contexts. *Neurophysiol. Clin.* 44 (2), 189–201. <https://doi.org/10.1016/j.neucli.2014.04.001>.
- Chang, F., Dell, G.S., Bock, K., 2006. Becoming syntactic. *Psychol. Rev.* 113 (2), 234–272. <https://doi.org/10.1037/0033-295x.113.2.234>.
- Connolly, J.F., Phillips, N.A., 1994. Event-related potential components reflect phonological and semantic processing of the terminal word of spoken sentences. *J. Cogn. Neurosci.* 6 (3), 256–266. <https://doi.org/10.1162/jocn.1994.6.3.256>.
- Cowan, N., 1995. *Attention And Memory: An Integrated Framework*. Oxford University Press, Oxford, UK.
- de Diego-Balaguer, R., Martinez-Alvarez, A., Pons, F., 2016. Temporal attention as a scaffold for language development. *Front. Psychol.* 7, 44. <https://doi.org/10.3389/fpsyg.2016.00044>.
- Deacon, D., Shelley-Tremblay, J., 2000. How automatically is meaning accessed: a review of the effects of attention on semantic processing. *Front. Biosci.* 5, E82–E94. <https://doi.org/10.2741/deacon>.
- Dell, G.S., Chang, F., 2014. The P-chain: relating sentence production and its disorders to comprehension and acquisition. *Philos. Trans. R. Soc. B Biol. Sci.* 369 (1634), 20120394. <https://doi.org/10.1098/rstb.2012.0394>.
- Dell, G.S., O’Seaghdha, P.G., 1992. Stages of lexical access in language production. *Cognition* 42 (1–3), 287–314. [https://doi.org/10.1016/0010-0277\(92\)90046-k](https://doi.org/10.1016/0010-0277(92)90046-k).
- DeLong, K.A., Urbach, T.P., Kutas, M., 2005. Probabilistic word pre-activation during language comprehension inferred from electrical brain activity. *Nat. Neurosci.* 8 (8), 1117–1121. <https://doi.org/10.1038/nn1504>.
- Dikker, S., Pylkkanen, L., 2013. Predicting language: MEG evidence for lexical preactivation. *Brain Lang.* 127 (1), 55–64. <https://doi.org/10.1016/j.bandl.2012.08.004>.
- Ditinger, E., Barbaroux, M., D’Imperio, M., Jancke, L., Elmer, S., Besson, M., 2016. Professional music training and novel word learning: from faster semantic encoding to longer-lasting word representations. *J. Cogn. Neurosci.* 28 (10), 1584–1602. https://doi.org/10.1162/jocn_a.00997.
- Ditinger, E., Chobert, J., Ziegler, J.C., Besson, M., 2017. Fast brain plasticity during word learning in musically-trained children. *Front. Hum. Neurosci.* 11, 233. <https://doi.org/10.3389/fnhum.2017.00233>.
- Ditinger, E., Scherer, J., Jancke, L., Besson, M., Elmer, S., 2019. Testing the influence of musical expertise on novel word learning across the lifespan using a cross-sectional approach in children, young adults and older adults. *Brain Lang.* 198, 104678. <https://doi.org/10.1016/j.bandl.2019.104678>.
- Dobel, C., Lagemann, L., Zwitserlood, P., 2009. Non-native phonemes in adult word learning: evidence from the N400m. *Philos.Trans.R.Soc.BBiol.Sci.* 364 (1536), 3697–3709. <https://doi.org/10.1098/rstb.2009.0158>.
- Duyck, W., Szmalec, A., Kemps, E., Vandierendonck, A., 2003. Verbal working memory is involved in associative word learning unless visual codes are available. *J. Mem. Lang.* 48 (3), 527–541. [https://doi.org/10.1016/S0749-596X\(02\)00533-8](https://doi.org/10.1016/S0749-596X(02)00533-8).
- Duzel, E., Yonelinas, A.P., Mangun, G.R., Heinze, H.J., Tulving, E., 1997. Event-related brain potential correlates of two states of conscious awareness in memory. *Proc. Natl. Acad. Sci. U. S. A.* 94 (11), 5973–5978. <https://doi.org/10.1073/pnas.94.11.5973>.
- Elgort, I., Perfetti, C.A., Rickles, B., Stafura, J.Z., 2015. Contextual learning of L2 word meanings: second language proficiency modulates behavioural and event-related brain potential (ERP) indicators of learning. *Lang.Cogn.Neurosci.* 30 (5), 506–528. <https://doi.org/10.1080/23273798.2014.942673>.
- Elman, J.L., 1991. Distributed representations, simple recurrent networks, and grammatical structure. *Mach. Learn.* 7 (2–3), 195–225. <https://doi.org/10.1023/A:1022699029236>.
- Elmer, S., Ditinger, E., Brocchetto, J., Francois, C., Besson, M., Jäncke, L., Rodriguez-Fornells, A., 2021. Phonetic skills and verbal memory capacity predict phonetic-based word learning: an event-related potential study. *J. Cogn. Neurosci.* https://doi.org/10.1162/jocn_a.01745 (accepted, in press).
- Emberson, L.L., Richards, J.E., Aslin, R.N., 2015. Top-down modulation in the infant brain: learning-induced expectations rapidly affect the sensory cortex at 6 months. *Proc. Natl. Acad. Sci. U. S. A.* 112 (31), 9585–9590. <https://doi.org/10.1073/pnas.1510343112>.
- Flanagan, J.R., Vetter, P., Johansson, R.S., Wolpert, D.M., 2003. Prediction precedes control in motor learning. *Curr. Biol.* 13 (2), 146–150. [https://doi.org/10.1016/S0960-9822\(03\)00007-1](https://doi.org/10.1016/S0960-9822(03)00007-1). Pii S0960-9822(03)00007-1.
- Francois, C., Cunillera, T., Garcia, E., Laine, M., Rodriguez-Fornells, A., 2017. Neurophysiological evidence for the interplay of speech segmentation and word-referent mapping during novel word learning. *Neuropsychologia* 98, 56–67. <https://doi.org/10.1016/j.neuropsychologia.2016.10.006>.
- Freunberger, D., Roehm, D., 2016. Semantic prediction in language comprehension: evidence from brain potentials. *Lang.Cogn.Neurosci.* 31 (9), 1193–1205. <https://doi.org/10.1080/23273798.2016.1205202>.
- Freundlieb, N., Ridder, V., Dobel, C., Enriquez-Geppert, S., Baumgaertner, A., Zwitserlood, P., Liuzzi, G., 2012. Associative vocabulary learning: development and testing of two paradigms for the (re-) acquisition of action- and object-related words. *Plos One* 7 (6), e37033. <https://doi.org/10.1371/journal.pone.0037033>.
- Friedman, D., 1990. Erps during continuous recognition memory for words. *Biol. Psychol.* 30 (1), 61–87. [https://doi.org/10.1016/0301-0511\(90\)90091-A](https://doi.org/10.1016/0301-0511(90)90091-A).
- Friedman, D., Cycowicz, Y.M., 2006. Repetition priming of possible and impossible objects from ERP and behavioral perspectives. *Psychophysiology* 43 (6), 569–578. <https://doi.org/10.1111/j.1469-8986.2006.00466.x>.
- Friedrich, M., Friederici, A.D., 2008. Neurophysiological correlates of online word learning in 14-month-old infants. *Neuroreport* 19 (18), 1757–1761. <https://doi.org/10.1097/WNR.0b013e328318f014>.
- Ganzach, Y., 1994. Feedback representation and prediction strategies. *Organ. Behav. Hum. Decis. Process.* 59 (3), 391–409. <https://doi.org/10.1006/obhd.1994.1066>.
- Gevins, A., Smith, M.E., 2000. Neurophysiological measures of working memory and individual differences in cognitive ability and cognitive style. *Cereb. Cortex* 10 (9), 829–839. <https://doi.org/10.1093/cercor/10.9.829>.
- Hagoort, P., 2014. Nodes and networks in the neural architecture for language: Broca’s region and beyond. *Curr. Opin. Neurobiol.* 28, 136–141. <https://doi.org/10.1016/j.conb.2014.07.013>.
- Holcomb, P.J., 1988. Automatic and attentional processing - an event-related brain potential analysis of semantic priming. *Brain Lang.* 35 (1), 66–85. [https://doi.org/10.1016/0093-934x\(88\)90101-0](https://doi.org/10.1016/0093-934x(88)90101-0).
- Hoshino, N., Thierry, G., 2012. Do Spanish-English bilinguals have their fingers in two pies - or is it their toes? An electrophysiological investigation of semantic access in bilinguals. *Front. Psychol.* 3, 9. <https://doi.org/10.3389/fpsyg.2012.00009>.
- Juottonen, K., Revonsuo, A., Lang, H.K., 1996. Dissimilar age influences on two ERP waveforms (LPC and N400) reflecting semantic context effect. *Cogn. Brain Res.* 4 (2), 99–107.

- Kiefer, M., 2008. Constraining unconscious cognition: top-down modulation of unconscious priming. *Int. J. Psychol.* 43 (3–4), 727–727.
- Kutas, M., Federmeier, K.D., 2011. Thirty years and counting: finding meaning in the N400 component of the event-related brain potential (ERP). *Annu. Rev. Psychol.* 62, 621–647. <https://doi.org/10.1146/annurev.psych.093008.131123>.
- Lau, E.F., Phillips, C., Poeppel, D., 2008. A cortical network for semantics: (de)constructing the N400. *Nat. Rev. Neurosci.* 9 (12), 920–933. <https://doi.org/10.1038/nrn2532>.
- Lau, E., Almeida, D., Hines, P.C., Poeppel, D., 2009. A lexical basis for N400 context effects: evidence from MEG. *Brain Lang.* 111 (3), 161–172. <https://doi.org/10.1016/j.bandl.2009.08.007>.
- Lau, E.F., Holcomb, P.J., Kuperberg, G.R., 2013. Dissociating N400 effects of prediction from association in single-word contexts. *J. Cogn. Neurosci.* 25 (3), 484–502. https://doi.org/10.1162/jocn_a.00328.
- Lefebvre, C.D., Marchand, Y., Eskes, G.A., Connolly, J.F., 2005. Assessment of working memory abilities using an event-related brain potential (ERP)-compatible digit span backward task. *Clin. Neurophysiol.* 116 (7), 1665–1680. <https://doi.org/10.1016/j.clinph.2005.03.015>.
- Lehrl, S.G.A., Blaha, L., Fischer, B., 1992. Kurztest fu r allgemeine Intelligenz (KAI). Vless, Ebersberg.
- Leon-Cabrera, P., Rodriguez-Fornells, A., Moris, J., 2017. Electrophysiological correlates of semantic anticipation during speech comprehension. *Neuropsychologia* 99, 326–334. <https://doi.org/10.1016/j.neuropsychologia.2017.02.026>.
- Leon-Cabrera, P., Flores, A., Rodriguez-Fornells, A., Moris, J., 2019. Ahead of time: early sentence slow cortical modulations associated to semantic prediction. *NeuroImage* 189, 192–201. <https://doi.org/10.1016/j.neuroimage.2019.01.005>.
- Levitt, W.J.M., Schriefers, H., Vorberg, D., Meyer, A.S., Pechmann, T., Havinga, J., 1991. The time course of lexical access in speech production - a study of picture naming. *Psychol. Rev.* 98 (1), 122–142. <https://doi.org/10.1037/0033-295x.98.1.122>.
- Maess, B., Friederici, A.D., Damian, M., Meyer, A.S., Levitt, W.J., 2002. Semantic category interference in overt picture naming: sharpening current density localization by PCA. *J. Cogn. Neurosci.* 14 (3), 455–462. <https://doi.org/10.1162/089892902317361967>.
- Mantegna, F., Hintz, F., Ostarek, M., Alday, P.M., Huettig, F., 2019. Distinguishing integration and prediction accounts of ERP N400 modulations in language processing through experimental design. *Neuropsychologia* 134, 107109. <https://doi.org/10.1016/j.neuropsychologia.2010.107109>.
- McLaughlin, J., Osterhout, L., Kim, A., 2004. Neural correlates of second-language word learning: minimal instruction produces rapid change. *Nat. Neurosci.* 7 (7), 703–704. <https://doi.org/10.1038/nn1264>.
- Mestres-Misse, A., Rodriguez-Fornells, A., Munte, T.F., 2007. Watching the brain during meaning acquisition. *Cereb. Cortex* 17 (8), 1858–1866. <https://doi.org/10.1093/cercor/bhl094>.
- Meyer, M., Elmer, S., Baumann, S., Jancke, L., 2007. Short-term plasticity in the auditory system: differential neural responses to perception and imagery of speech and music. *Restor. Neurol. Neurosci.* 25 (3–4), 411–431.
- Missonnier, P., Leonards, U., Gold, G., Palix, J., Ibanez, V., Giannakopoulos, P., 2003. A new electrophysiological index for working memory load in humans. *Neuroreport* 14 (11), 1451–1455. <https://doi.org/10.1097/00001756-200308060-00009>.
- Molholm, S., Martinez, A., Shpaner, M., Foxe, J.J., 2007. Object-based attention is multisensory: co-activation of an object's representations in ignored sensory modalities. *Eur. J. Neurosci.* 26 (2), 499–509. <https://doi.org/10.1111/j.1460-9568.2007.05668.x>.
- Morgan, H.M., Jackson, M.C., Klein, C., Mohr, H., Shapiro, K.L., Linden, D.E., 2010. Neural signatures of stimulus features in visual working memory—a spatiotemporal approach. *Cereb. Cortex* 20 (1), 187–197. <https://doi.org/10.1093/cercor/bhp094>.
- Moris, J., Luque, D., Rodriguez-Fornells, A., 2013. Learning-induced modulations of the stimulus-preceding negativity. *Psychophysiology* 50 (9), 931–939. <https://doi.org/10.1111/psyp.12073>.
- Okita, T., Jibu, T., 1998. Selective attention and N400 attenuation with spoken word repetition. *Psychophysiology* 35 (3), 260–271. <https://doi.org/10.1017/S0048577298961042>.
- Otten, L., 1996. Attention and memory: an integrated framework - Cowan. *N. Biol. Psychol.* 44 (1), 59–61. [https://doi.org/10.1016/S0301-0511\(96\)05264-7](https://doi.org/10.1016/S0301-0511(96)05264-7).
- Packard, P.A., Rodriguez-Fornells, A., Bunzeck, N., Nicolas, B., de Diego-Balaguer, R., Fuentes-Milla, L., 2017. Semantic congruence accelerates the onset of the neural signals of successful memory encoding. *J. Neurosci.* 37 (2), 291–301. <https://doi.org/10.1523/Jneurosci.1622-16.2017>.
- Paller, K.A., Kutas, M., 1992. Brain potentials during memory retrieval provide neurophysiological support for the distinction between conscious recollection and priming. *J. Cogn. Neurosci.* 4 (4), 375–391. <https://doi.org/10.1162/jocn.1992.4.4.375>.
- Perfetti, C.A., Wlotko, E.W., Hart, L.A., 2005. Word learning and individual differences in word learning reflected in event-related potentials. *J. Exp. Psychol. Learn. Mem. Cogn.* 31 (6), 1281–1292. <https://doi.org/10.1037/0278-7393.31.6.1281>.
- Pickering, M.J., Garrod, S., 2014. Self-, other-, and joint monitoring using forward models. *Front. Hum. Neurosci.* 8, 132. <https://doi.org/10.3389/fnhum.2014.00132>.
- Pulvermuller, F., Grisoni, L., 2020. Semantic prediction in brain and mind. *Trends Cogn. Sci.* 24 (10), 781–784. <https://doi.org/10.1016/j.tics.2020.07.002>.
- Reuter, T., Borovsky, A., Lew-Williams, C., 2019. Predict and redirect: prediction errors support children's word learning. *Dev. Psychol.* 55 (8), 1656–1665. <https://doi.org/10.1037/dev0000754>.
- Rodriguez-Fornells, A., Cunillera, T., Mestres-Misse, A., de Diego-Balaguer, R., 2009. Neurophysiological mechanisms involved in language learning in adults. *Philos. Trans. R. Soc. Lond. Ser. B Biol. Sci.* 364 (1536), 3711–3735. <https://doi.org/10.1098/rstb.2009.0130>.
- Rohaut, B., Faugeras, F., Chausson, N., King, J.R., El Karoui, I., Cohen, L., Naccache, L., 2015. Probing ERP correlates of verbal semantic processing in patients with impaired consciousness. *Neuropsychologia* 66, 279–292. <https://doi.org/10.1016/j.neuropsychologia.2014.10.014>.
- Roll, M., Soderstrom, P., Frid, J., Mannfolk, P., Horne, M., 2017. Forehearing words: pre-activation of word endings at word onset. *Neurosci. Lett.* 658, 57–61. <https://doi.org/10.1016/j.neulet.2017.08.030>.
- Rugg, M.D., 1985. The effects of semantic priming and work repetition on event-related potentials. *Psychophysiology* 22 (6), 642–647. <https://doi.org/10.1111/j.1469-8986.1985.tb01661.x>.
- Rugg, M.D., 1990. Event-related brain potentials dissociate repetition effects of high-frequency and low-frequency words. *Mem. Cogn.* 18 (4), 367–379. <https://doi.org/10.3758/BF03197126>.
- Rugg, M.D., Curran, T., 2007. Event-related potentials and recognition memory. *Trends Cogn. Sci.* 11 (6), 251–257. <https://doi.org/10.1016/j.tics.2007.04.004>.
- Ruz, M., Nobre, A.C., 2008. Attention modulates initial stages of visual word processing. *J. Cogn. Neurosci.* 20 (9), 1727–1736. <https://doi.org/10.1162/jocn.2008.20119>.
- Schultz, W., Dickinson, A., 2000. Neuronal coding of prediction errors. *Annu. Rev. Neurosci.* 23, 473–500. <https://doi.org/10.1146/annurev.neuro.23.1.473>.
- Soderstrom, P., Horne, M., Frid, J., Roll, M., 2016. Pre-activation negativity (PrAN) in brain potentials to unfolding words. *Front. Hum. Neurosci.* 10, 512. <https://doi.org/10.3389/fnhum.2016.00512>.
- Staresina, B.P., Gray, J.C., Davachi, L., 2009. Event congruency enhances episodic memory encoding through semantic elaboration and relational binding. *Cereb. Cortex* 19 (5), 1198–1207. <https://doi.org/10.1093/cercor/bhn165>.
- Takahshima, A., Bakker, I., van Hell, J.G., Janzen, G., McQueen, J.M., 2017. Interaction between episodic and semantic memory networks in the acquisition and consolidation of novel spoken words. *Brain Lang.* 167, 44–60. <https://doi.org/10.1016/j.bandl.2016.05.009>.
- Talsma, D., Doty, T.J., Woldorff, M.G., 2007. Selective attention and audiovisual integration: is attending to both modalities a prerequisite for early integration? *Cereb. Cortex* 17 (3), 679–690. <https://doi.org/10.1093/cercor/bhk016>.
- Van Berkum, J.J.A., 2009. The neuropragmatics of simple utterance comprehension: an ERP review. In: *Semantics And Pragmatics: From Experiment to Theory*. Palgrave Macmillan, Basingstoke, pp. 276–316.
- Van Berkum, J.J.A., 2010. The brain is a prediction machine that cares about good and bad - any implications for neuropragmatics? *Ital. J. Linguist.* 22, 181–208.
- van den Brink, D., Brown, C.M., Hagoort, P., 2001. Electrophysiological evidence for early contextual influences during spoken-word recognition: N200 versus N400 effects. *J. Cogn. Neurosci.* 13 (7), 967–985. <https://doi.org/10.1162/089892901753165872>.
- van Kesteren, M.T.R., Rijpkema, M., Ruiters, D.J., Morris, R.G.M., Fernandez, G., 2014. Building on prior knowledge: schema-dependent encoding processes relate to academic performance. *J. Cogn. Neurosci.* 26 (10), 2250–2261. https://doi.org/10.1162/jocn_a.00630.
- Van Petten, C., 2014. Examining the N400 semantic context effect item-by-item: relationship to corpus-based measures of word co-occurrence. *Int. J. Psychophysiol.* 94 (3), 407–419. <https://doi.org/10.1016/j.ijpsycho.2014.10.012>.
- Van Petten, C., Luka, B.J., 2012. Prediction during language comprehension: benefits, costs, and ERP components. *Int. J. Psychophysiol.* 83 (2), 176–190. <https://doi.org/10.1016/j.ijpsycho.2011.09.015>.
- Van Petten, C., Coulson, S., Rubin, S., Plante, E., Parks, M., 1999. Time course of word identification and semantic integration in spoken language. *J. Exp. Psychol. Learn. Mem. Cogn.* 25 (2), 394–417. <https://doi.org/10.1037/0278-7393.25.2.394>.
- Voss, J.L., Federmeier, K.D., 2011. FN400 potentials are functionally identical to N400 potentials and reflect semantic processing during recognition testing. *Psychophysiology* 48 (4), 532–546. <https://doi.org/10.1111/j.1469-8986.2010.01085.x>.
- Wagner, A.D., Schacter, D.L., Rotte, M., Koutstaal, W., Maril, A., Dale, A.M., Buckner, R.L., 1998. Building memories: remembering and forgetting of verbal experiences as predicted by brain activity. *Science* 281 (5380), 1188–1191. <https://doi.org/10.1126/science.281.5380.1188>.
- Wilding, E.L., Rugg, M.D., 1996. An event-related potential study of recognition memory with and without retrieval of source (vol 119, pg 889, 1996). *Brain* 119. <https://doi.org/10.1093/brain/119.4.1415-a>, 1416–1416.
- Zwitserslood, P., Bolte, J., Hofmann, R., Meier, C.C., Döbel, C., 2018. Seeing for speaking: semantic and lexical information provided by briefly presented, naturalistic action scenes. *Plos One* 13 (4), e0194762. <https://doi.org/10.1371/journal.pone.0194762>.