Visual mismatch negativity indexes automatic lexicality detection

Bernard A. J. Jap[1]*, Stephen Politzer-Ahles[2]

[1] School of Arts and Social Sciences, Hong Kong Metropolitan University, Hong Kong

[2] Department of Linguistics, University of Kansas, United States

* Corresponding author

E-mail: bajjap@hkmu.edu.hk (BAJJ)

ORCID

BAJJ: 0000-0001-5276-9805

SPA: 0000-0002-5474-7930

Abstract

This study explores the automatic processing of lexicality and abstract linguistic contrasts using visual mismatch negativity (vMMN). Prior research has shown that auditory mismatch negativity is sensitive to abstract linguistic contrast, but it remains unclear if similar effects occur through the visual domain. Similarly, there is some evidence of lexicality effects via vMMN, but previous work did not seem to fully claim that lexicality detection is observed independent of attention. We investigated whether lexicality contrasts (words and pseudowords) and abstract contrasts between word classes could elicit vMMNs. Our findings indicate that lexicality can generate vMMNs, with significant ERP effects observed for word contrasts. However, no vMMN was detected for the abstract contrast between nouns and verbs. These results suggest that while lexical processing can occur rapidly and automatically in the visual modality (extending predictive coding accounts to include pre-attentive lexical-level representations), abstract processing of visual linguistic information warrants further investigation.

Keywords: visual mismatch negativity (vMMN), abstract linguistic processing, lexicality, event-related potential (ERP)

Introduction

A key question in neurolinguistics lies on when precisely the brain accesses word representations and whether this process is automatic. Traditionally, lexico-semantic access has been thought to occur around 350–400 ms after seeing or hearing a word (Friederici, 2002; Hagoort, 2007). However, other authors have since reported findings that suggest these processes may begin much earlier, at around 50–200 ms (He et al., 2022; Pulvermüller et al., 2009). Similarly, there is growing support for a degree of automaticity in early lexico-semantic and syntactic processes, challenging previous assumptions about the necessity of attentional control (Krauska & Lau, 2023; Krivochen, 2014).

To investigate the automaticity of processing lexico-semantic information, many have utilized the mismatch negativity (MMN), an early component of auditory event-related potentials (ERP) that shows high sensitivity to unexpected changes in unattended stimuli. The MMN is typically elicited using an oddball paradigm, where two types of stimuli are repeatedly presented: one type occurs frequently (standards) and the other infrequently (deviants). When a deviant stimulus is presented, the MMN appears as a more negative event-related potential compared to the standard stimulus. This response occurs because the brain detects a mismatch between the incoming stimulus and the memory representation of recent stimuli (Näätänen et al., 2007), or because it updates a predictive model when an unexpected stimulus is encountered (Bornkessel-Schlesewsky & Schlesewsky, 2019; Winkler, 2007).

The MMN is a well-established and extensively utilized ERP component in research, used to study language processing, language acquisition, autism, and various neuropsychological conditions (Eulitz & Lahiri, 2004; Lu et al., 2015; O'Connor, 2012; Schall, 2016; Zarza et al., 2007). Its effectiveness lies in its sensitivity to psychological differences. For instance, one study (Phillips et al., 2000) found that English speakers exhibit an MMN response to a series of sounds that do not form an oddball paradigm in terms of their physical features, but do form one in terms of the phonological categories they fall into. However, if the same level of physical variation is present in a series of sounds that do not form an oddball paradigm based on their phonological categorization, the MMN response is absent. Additionally, Kazanina and colleagues (2006) showed that Russian speakers, but not Korean speakers, displayed an MMN for a contrast that is meaningful in Russian but not in Korean.

These results suggest that the brain's change detection process, as indicated by the MMN, incorporates the individual's language knowledge. The brain categorizes incoming stimuli, makes predictions about future stimuli, and updates its predictive model when predictions are incorrect (Bornkessel-Schlesewsky & Schlesewsky, 2019), all without the individual's conscious attention.

Visual mismatch negativity and automatic lexical processing

When sounds are in the form of meaningful speech elements, they elicit a characteristic ERP amplitude increase called "lexical enhancement," typically occurring around 100-200 ms (He et al., 2022; Shtyrov et al., 2008). This response has been shown to be sensitive to various lexical properties and has led to conclusions that it reflects the activation of neural memory traces for stimulus words (Shtyrov et al., 2013).

While auditory studies have provided substantial evidence for early automatic lexical activation, visual experiments have typically presented stimuli in the focus of attention, making it difficult to address questions of automaticity.

One way to bridge the gap is to adapt auditory MMN paradigms for the visual modality. The visual mismatch negativity (vMMN), an analogue of the auditory MMN, has been observed for non-linguistic graphical stimuli and can be elicited independently of attention (Astikainen et al., 2022; Petro et al., 2023) by deviations in various visual features including color (Czigler et al., 2002), orientation (Astikainen & Hietanen, 2009; Kimura et al., 2010), movement (Pazo-Alvarez et al., 2003), spatial frequency (Heslenfeld, 2003), contrast (Stagg et al., 2004), and even abstract sequential regularities (e.g., "if, then..." rules; Stefanics et al., 2011) in visual stimulation. While vMMN has been associated with neural mechanisms of automatic visual change detection and short-term memory (Czigler & Pato, 2009), it remains largely unexplored regarding its sensitivity to long-term representations, such as word-specific lexical memory circuits (Stefanics et al., 2014; Winkler & Czigler, 2012). Furthermore, visual presentation also overcomes some inherent problems of spoken stimulus presentation such as timing of stimulus duration for certain types of stimuli (Male et al., 2020).

Shtyrov et al. (2013) investigated the automaticity of lexical processing and found that unattended words elicited ERPs when compared to pseudowords, starting early on at 100 ms. This supports the notion of early and automatic lexical processing in the visual domain, suggesting that lexical memory traces can be activated rapidly and without attention.

However, there are some reservations regarding the outcome of the study. First, the use of perifoveal presentation of stimuli could introduce variability in visual acuity and attention that is difficult to control, specifically, some components like the late positive complex (LPC) are affected by vision angle and not elicited even parafoveally (Li et al., 2024). In relation to vMMN, in one study (Petro et al., 2023), central (foveal) presentation of the stimuli with task-related and task-unrelated stimuli being separated temporally produces a large deviant-standard ERP, while parafoveal presentation did not result in detectable vMMNs.

Second, while the study shows that words elicited a different ERP on average than nonwords, it does not show that participants were pre-attentively sensitive to the *contrast* between words and nonwords. Words elicited different ERPs than pseudowords regardless of whether they were standards or deviants; likewise, deviants elicited MMNs relative to standards, and the magnitude of this MMN did not differ as a function of whether the deviants and standards were words or pseudowords. Shtyrov and colleagues (2013) tested all possible combinations—word standard – word deviant, pseudoword standard – pseudoword deviant, word – pseudoword, and pseudoword – word—and all these combinations elicited similar MMN effects. The physical difference between standard and deviant in these situations was always the same (standards ended with a К and deviants with a H), so the MMN effect was due to the physical difference rather than to lexical status. In other words, it is possible that words and pseudowords would have elicited the same differences if they were not presented in an MMN oddball paradigm at all, but were just mixed randomly. The fact that words and pseudowords elicit different ERPs does not necessarily mean that the brain pre-attentively categorizes them in a way that would elicit a (v)MMN.

Finally, the study may not have had sufficient statistical power to reliably separate components related to lexicality processing from noise; while the number of trials per condition (deviants and critical standards) was not revealed, the sample size of 16 is relatively small for a vMMN study involving higher-level processing which is required for words and lexicality. In comparison, other studies successfully eliciting word-level vMMNs have generally involved over 20 participants per group (Hu et al., 2020; Wei et al., 2018).

Abstract processing of linguistic stimuli

Previous research has demonstrated that the MMN's sensitivity to auditory changes is influenced by linguistic knowledge. For instance, Phillips et al. (2000) and Kazanina et al. (2006) showed that MMN can be influenced by phonological categories specific to a listener's language. However, these studies did not conclusively demonstrate that purely abstract linguistic contrasts, without any physical acoustic differences, can elicit MMN.

In a registered report, Politzer-Ahles and Jap (2024) investigated whether MMN can be elicited by abstract linguistic contrasts devoid of reliable acoustic cues by utilizing contrasts in English verb tenses marked by ablaut or vowel changes (e.g. for the past deviant and present standard block, they presented *gave*, *met*, and *sank* as deviant stimuli and *pave*, *get*, *thank* as critical standards in addition to several other present-tense filler verbs as extra standards; a block might look like: *gave met sank chose sand bled* ***pave****...*). Their findings indicated that purely abstract linguistic contrasts could indeed elicit MMN, supporting the notion that MMN is sensitive to higher-level linguistic processing. There are no equivalent studies that we are aware of on the visual counterpart of MMN that test this strongest possible interpretation of the abstract processing claim.

Hu et al. (2020) conducted a vMMN study where participants were exposed to oddball sequences of Chinese characters, with deviant words differing in semantic categories from the standard words (e.g., action words versus color words). They reported observing a visual mismatch negativity in response to these semantic contrasts, although this finding was arguably influenced by their choice of time window used in the analysis. The primary aim of their research was to investigate the extraction of semantic information from radicals—orthographic components of Chinese characters. Therefore, they used stimuli where the semantic contrast was also indicated by the presence of a radical. Notably, in an experiment that used stimuli without semantic radicals, no vMMN was observed. Therefore, this study does not definitively demonstrate that the vMMN can be generated based on purely abstract linguistic contrasts (i.e., without an orthographic cue).

The present study

The present study has two goals: (1) To investigate whether lexicality effects can generate reliable vMMNs (2) To test the visual analogue of the "abstract" MMN elicited through auditory stimuli (Politzer-Ahles & Jap, 2024): can vMMNs be generated by abstract linguistic contrasts?

Previous auditory MMN research demonstrates sensitivity to abstract linguistic contrasts (e.g., tense distinctions; Politzer-Ahles & Jap, 2024), but analogous evidence in the visual domain remains scarce. Critically, prior visual studies (e.g., Shtyrov et al., 2013) tested ERP differences between individual words and pseudowords with explicit physical contrasts (e.g., final letters), leaving unresolved whether the brain detects lexicality *as an abstract category*. For instance, Shtyrov et al.'s (2013) design could not disentangle physical deviance (e.g., "K" vs. "H" endings) from lexical mismatch, as every deviant-standard pair differed orthographically. In contrast, our paradigm tests whether the brain pre-attentively distinguishes *sets* of words and pseudowords where lexicality is the sole systematic contrast, with no reliable physical differences between categories. This advances a theoretically distinct question: Does automatic detection of lexical status rely on abstract linguistic representations, or merely on low-level orthographic familiarity?

We have also ensured that our vMMN design is methodologically sound by implementing: (1) foveal (central) presentation, which has been shown to more reliably generate vMMNs under different task conditions (Petro et al., 2023); (2) a task that has been applied to visual word presentation in an oddball paradigm (Hu et al., 2020); (3) a set of stimuli that incorporates additional standards and multiple deviant and critical standard tokens to prevent participants from tracking orthographic features; and (4) sufficient sample size for reasonable statistical power.

As for the second (2) research question, the most compelling evidence for this effect would be a vMMN generated in a scenario where the deviant and standard stimuli belong to different linguistic categories without any reliable physical cues differentiating them. Observing a vMMN in such a context would broaden our understanding of the types of information and representations the brain can process without deliberate attention. In the auditory abstract MMN study (Politzer-Ahles & Jap, 2024), the authors elicited MMN by presenting a morphosyntactic distinction with no reliable physical contrast – using past- and present-tense ablauting irregular English verbs. In this study, we attempt to elicit a visual equivalent by presenting a word class contrast between Standard Indonesian (SI) verbs and nouns that only differ visually by their final letter. We consider the word class contrast to be more 'abstract' than the word-pseudoword contrast, as distinguishing grammatical class requires access to the linguistic properties and lexical specification of the word, where this higher-level process generated relatively later ERPs like the LAN and N400 (Yudes et al., 2016). In comparison, word-pseudoword distinctions can be based on familiarity of orthographic form, for instance, participants have seen and will recognize the words in their language but not the novel, newly presented pseudowords. These more basic, lower-level processes to word recognition invoke earlier ERPs like the P150 and N200 (Coch & Mitra, 2010), which are associated with orthographic familiarity and lexicality, respectively.

This study not only offers methodological improvements—such as foveal presentation, a robust oddball paradigm design, and a larger sample size—but also provides theoretical contributions. Previous related work (Shtyrov et al., 2013) showed that visual word forms with physical correlates differ in ERP responses, but it remained unclear whether these differences were driven by genuine mismatch detection at the lexical level. By demonstrating a reliable vMMN that is elicited by words in a controlled paradigm, our data can extend predictive coding accounts of perception. Specifically, the study may suggest that lexical-level predictions, stored in the mental lexicon, can be activated under unattended conditions and lead to prediction error signals when violated.

Method

Participants

We recruited 50 participants who are first-language speakers of Indonesian (Age *M*= 34.68;range=22-46; *SD*=6.13, all female). Of these 50 participants, 10 were excluded because of having insufficient trials remaining for analysis. Only participants with at least 20 trials per condition out of 45 are included in the analyses. They are right-handed through self-reported questionnaire and neurotypical with unimpaired or corrected vision. Participants were adequately informed of the experiment procedure, signed an informed consent form prior to the start of the experiment, and were financially compensated for their time (150HKD). This protocol has received ethics approval from the institutional review board of the Research and Innovation Office at the Hong Kong Polytechnic University (#HSEARS20180409003).

Power

We did not have comparable vMMN data (lexical processing or abstract linguistic contrast) to run a power analysis, as such, when estimating the number of participants and trials for sufficient statistical power in our analysis, we compared our target effect conservatively to the lateralized readiness potential (LRPs), a typically small component (Smulders & Miller, 2012) at around 1-4 μV which has clear guidelines for statistical power. A previous study (Boudewyn et al., 2018) argued that having at least 32 participants and 45 trials per condition was both (1) sufficient for a high level of internal reliability for the ERP with a Cronbach's alpha of 0.7-0.9 (2) sufficient to detect even relatively small ERP differences in within-subject experiment designs: Monte Carlo between-condition simulations showing effects of 0.75 μV at over 90% probability while effects of 1 μV, 1.25 μV and 1.5μV all have peak (100%) probabilities of achieving $p<.05$. Effects larger than 1.5 μV will achieve peak probability with as few as 20 participants, whereas effects smaller than 0.75 μV (e.g. 0.5 μV and 0.25 μV) do experience improvement in the probability of detecting a difference with larger sample sizes (with the range between 12 and 32 participants) but remains lower than 0.8 (80%). A similar study (Politzer-Ahles & Jap, 2024) on abstract MMNs calculated power using an effect size of $d = -0.37$ with a mean amplitude of -0.84μV ($SD = 2.28$). As such, we believe that the present study, by approximately matching this estimation derived from a small-magnitude ERP with 40 participants and 45 trials per condition (after pre-processing, an average of 39.3 [SD=4.62] artifact-free trials per participant per condition) can detect subtle vMMNs elicited by high-level processing in our current study and provides us with reasonable statistical power to detect small effect magnitudes, provided there is a *true* difference between the deviants and standards of at least 0.75 μV (around 90% with our sample size and trial number).

Materials

The stimuli are shown in Table 1. We presented 2 separate contrasts, namely, word class (verb/noun) and lexicality (word/pseudoword). For the word class contrast, we selected a relatively frequent set of three unambiguous nouns and three unambiguous base-form-verbs (frequency is extracted from the *Indonesian mixed corpus,* a part of the Leipzig Corpora Collection (Goldhahn et al., 2012) Table 2). The words used as deviants in one block were used as critical standards in another block and vice versa. This means the analyses involved comparing words which appeared as deviants in one block to the same words appearing as standards in a different block. The nouns and verbs differ from each other only in the final grapheme, and as far as we can observe, there are no systematic orthographic or phonological difference between these two sets. We avoided homophones (e.g. *magang* can mean an intern [noun] or over-ripe [adj]).

Additionally, we added a set of extra filler standards for each block. This is done to prevent the participants from tracking individual word frequencies, which could also elicit a vMMN. For example, in a block where nouns (*pakar, bakat, tarif* [expert, talent, fee]) are deviants and verbs (*pakai, bakar, tarik* [use, burn, pull]) are standards, if the three verbs are presented more frequently than the three nouns, the participants could simply notice the fact that the latter set of words occur much more frequently in the block—which might be sufficient to elicit a vMMN without any influence of the abstract linguistic contrast between these two groups of words. As such, we added nine additional verbs to become extra standards, whereby the block includes twelve standard items and three deviant items. This ensures that *verbs* are presented more frequently than *nouns* in the block, but no particular word is presented more frequently than any other; thus, the only way participants could notice that there are standards and deviants is to notice the abstract lexical category of the words. The frequency of each token outside of the deviants and critical standards were randomized as such participants could not recognize the oddball arrangement by noting how often a specific word is repeated, and the only way the brain detects this contrast is from the fact that most of the stimuli inside the block are verbs while only a few are nouns.

Table 1 here

Table 2 here

The lexicality contrast between words and pseudowords involves one block with words as deviants and pseudowords and standards, and another with the opposite. The pseudoword stimuli are modifications of the word stimuli, with the final grapheme changed resulting in an entity that is a pseudoword (a non-word that is composed of phonemes that are 'legal' in Indonesian phonotactics and therefore somewhat resemble a word, but has, in fact, no meaning in the lexicon). All stimuli in the first four blocks have 5 graphemes and 2 syllables. We expect to find at least a vMMN in the lexicality block, as this contrast has been reported multiple times to elicit ERPs (Petro et al., 2023; Shtyrov et al., 2013).

Procedure

Participants read the information sheet and filled out a demographic questionnaire and the informed consent form. While the EEG cap was being prepared, the experimenter explained to the participant that they will be pressing a button in reaction to a change in the fixation cross. During the experiment, participants had multiple opportunities for breaks (between each block, which lasted approximately 5 minutes each), and they could blink normally but were asked to avoid closing their eyes for an extended period of time, and to attempt to sit still until a between-block break.

The stimuli were presented in white font on the centre of a grey screen. The presentation duration of each stimuli was 300ms and the interstimulus interval was 600ms with a randomized jitter of 0-20ms (meaning the ISI was between 600-620ms). In each block, there were 45 deviants (15 trials for each unique item) and 45 critical standards (15 for each item). Accounting for the extra standards, the ratio between standards and deviants was approximately 85:15 for each block. At least 20 standards were presented at the beginning of each block before any deviant tokens were presented. Following this, each deviant was always preceded by 4 to 9 standards. Each block ended with a standard.

Participants were instructed to ignore the experimental stimuli and to press a button using their right index finger as quickly and accurately as possible when detecting a change in the fixation cross that was presented in the middle of the word. We used a cross-detection task that has argued to elicit vMMNs while presenting single-words/characters in previous experiments (Hu et al., 2020). The fixation cross (2.3cm x 2.3cm) changes by either having a longer vertical line or a longer horizontal line. The cross change itself never occurs within 1800ms before or after 900ms after the onset of a deviant or a critical standard: this is done to anticipate the possible influence of a motor movement or task-related brain response when looking at the ERPs in the deviants and critical standards. There were 50 fixation cross changes per block, and the experiment lasted for approximately 30 minutes per participant.

Each type of block occurred once, and blocks were presented in two pseudorandomized lists. Each participant only viewed one of the lists. The presentation of stimulus and recording of triggers to the acquisition program were conducted through EPrime 2 (Psychology Software Tools).

EEG acquisition and preprocessing

EEGs were recorded using 64 Ag-AgCl electrodes that were attached to the participant's scalp via an elastic cap with a 10-20 system. Conductive gel was used. The cap had two dedicated electrodes for the left and right mastoids. To monitor horizontal and vertical eye movements, two electrodes were fixed in the outer canthi of each eye, and one more was placed below the left eye (the VEOG above the left eye is integrated in the cap). Electrode impedances were kept below 5 kΩ. The EEG was amplified and digitized with a sampling rate of 1000 Hz with an analog bandpass filter of 0.03-100Hz. The amplifier used was a SynAmps 2 (NeuroScan, Charlotte, NC, United States), and the cap was a 64-channel Quik-Cap Neo Net (NeuroScan, Charlotte, NC, United States). A Stimtracker (Cedrus) provided an interface between the experiment presentation software and EEG acquisition. Continuous EEG data were acquired using Curry 7 acquisition software (Compumedics NeuroScan) whereby the files were exported to the .cnt format and analysed using EEGLAB (Delorme & Makeig, 2004) for preprocessing, and FieldTrip (Oostenveld et al., 2011) for the statistical analysis.

The continuous data were re-referenced to the average of both mastoids and segmented into epochs from 150 ms before and 750 ms after onset. These values were chosen to ensure that the epochs can be as long as possible without overlapping with adjacent epochs, given the 300ms word presentation plus the 600-620ms ITI. These epochs were then demeaned per channel in each epoch (the mean of the data from the entire epoch was subtracted from each data point, as this may result in better ICA decompositions than baseline-correcting based on pre-stimulus interval (Groppe et al., 2011). The epochs were then subjected to an independent component analysis using the runica() command in EEGLAB (Makeig et al., 1997); this divided the data into many independent components corresponding to the number of channels, excluding mastoid electrodes, EOGs, and bad channels that were previously marked. These components were automatically identified using the *IClabel*() command (Pion-Tonachini et al., 2019a) in EEGLAB. *ICLabel* is an algorithm that utilizes machine learning to identify artifactual ICA components through topography and activity patterns. It assigns each component a probability indicating its likelihood of belonging to one of seven distinct classes, which include artifact categories such as muscle and eye movement (Pion-Tonachini et al., 2019b). A threshold was applied to detect and remove artifacts with a probability of 0.9 (90%) to be assigned as eye or muscle components. This is a default conservative value recommended in optimized preprocessing pipelines (Delorme, 2023). After the removal of components, baseline correction was applied to the data with a 150 ms pre-stimulus-onset baseline. Next, the epochs were run through a moving-window peak-to-peak threshold function (window size of 200ms with a window step of 50ms and a threshold of 80μV) for artefact detection; epochs with artifacts were marked for removal based on this criterion. Finally, a 30 Hz low-pass filter (using the default settings of the EEGLAB function pop_eegfiltnew) was applied.

For each condition, the vMMN is calculated by comparing the ERP elicited by tokens when they are presented as standards to the ERP elicited by those same tokens when they are presented as deviants. For example, to test whether verb deviants yield a vMMN, we compared the average of the ERPs for (*pakai, bakar, tarik* [use, burn, pull]) when they were deviants, to the average of the ERPs for (*pakai, bakar, tarik* [use, burn, pull]) when they were standards. A more negative ERP response to these words when used as deviants than when used as standards would be indicative of a vMMN.

Within the lexicality contrast, we tested the main effect of standard vs. deviant (i.e., whether there is a vMMN at all for this contrast) by comparing the deviants to the standards. As described above, this ensures that ERPs elicited by identical stimuli are compared (a stimulus that occurs as standards in one block also occurs as deviants in another block), and since the analysis includes both words and pseudowords this collapses across both directions of the contrast. To see whether one direction of contrast (word standards to pseudoword deviants, vs. pseudoword standards to word deviants) elicits a larger vMMN, we tested the interaction by calculating a vMMN difference wave for each contrast (pseudoword deviant minus pseudoword standard, word deviant minus word standard) and comparing these to each other. Finally, we tested simple effects of standard-deviant within each contrast (whether pseudoword deviants elicit more negative ERPs than pseudoword standards, and whether word deviants elicit more negative ERPs than word standards) by directly comparing the deviant to the standard within that contrast. We report the simple effects for the sake of completeness, but they are to be treated as tentative and exploratory if the interaction is not statistically significant.

We followed the same procedure to test the main effect, interaction, and simple effects within the verb-noun contrast. The following section explains how each of these comparisons was carried out statistically.

Statistical analysis

The statistical analysis was conducted using cluster-based permutation tests (Maris & Oostenveld, 2007) over all the scalp electrodes in the vMMN time window of 100 to 400ms. The advantage of this approach is that it allows testing for effects anywhere on the scalp and any time in the epoch, while still controlling the familywise false positive rate, and without the experimenter needing to choose regions or time windows for generating mean amplitudes. The test works by comparing a pair of ERPs at each channel and each sample, and identifying clusters of spatiotemporally adjacent data points where the difference between the two conditions exceeds some threshold; in our analysis, that threshold is one-tailed $p<.05$ in a t-test for the whole epoch.

In other words, a t-test comparing two ERPs was performed at every sample in every channel (note that sometimes the comparison was between standards and deviants, but for the interaction test the comparison was between vMMN difference waves), and if a series of several time points in a row on the same channel and/or several adjacent channels at the same time all meet the uncorrected one-tailed $p<.05$ threshold, they are treated as a "cluster". For any sample to be included in a cluster, it needed to have at least two spatial neighbouring electrodes that also meet the threshold (we used the *minnbchan=2* function in the Fieldtrip implementation of the cluster-based test). Next, each cluster is assigned a test statistic (in our case, the test statistic for a cluster is derived by summing the *t*-values of all the samples in the cluster), and the largest cluster-level test statistic in the epoch is taken as the observed test statistic for the data. Next, the data are randomly permuted (i.e., within each subject, the condition labels "deviant" and "standard" may be randomly switched) several thousand times, and with each random permutation the abovementioned procedure of identifying clusters and calculating a test statistic is repeated. This yields a permutation distribution of several thousand test statistics, against which the original observed test statistic is compared. The proportion of permutation test statistics that are larger than the original observed test statistic is the *p*-value for the test; if there is a significant difference between the deviant and standard ERPs then this value will be small (in other words, if there is a robust difference between deviants and standards in the real data, then random permutations of the data will rarely show a bigger difference than the real difference). The permutation tests used 5000 iterations.

Results

Participants completed the fixation cross-change detection task with an "accuracy" rate of 92% (SD = 0.29) and a mean reaction time from onset of cross change of 647 ms (SD = 377.5). We define "accuracy" here as participants responding within 5000 ms of the cross changing. Failing to respond within 5000 ms was coded as an 'inaccurate' trial.

Figure 1 shows ERPs in channels displaying effects in response to the lexicality contrast. Using cluster-based permutation tests, we did not observe a significant ERP on the collapsed analysis of the lexicality contrast (p=0.051; 280ms to 365ms; 37 channels; see Figure 2 for the distribution of this effect). The lexicality interaction test, a comparison between vMMN difference waves, was not significant (p=0.419). However, in the exploratory analysis of simple effects we found a significant vMMN for word deviants (Figure 1; p=0.021) with this difference being driven by a cluster showing a frontocentral broadly distributed (across 42 electrodes) negative shift from 275ms to 400ms . On the other hand, pseudoword (Figure 1) deviants did not elicit a significant vMMN (p=0.632) in this exploratory analysis.

Figure 1 here

Figure 2 here

We did not observe any significant standard-deviant differences in the word class contrast (no negative clusters were identified for the main effect and individual tests) and individually as nouns and verbs (Figure 3 shows the waveform and topographical plots for the word class contrast collapsed across conditions).

Figure 3 does show an apparent *positivity* for noun deviants, compared to noun standards. An exploratory one-tailed cluster test revealed a very marginal effect for this contract (p=.100). This suggests that some other component (such as P3) may have been sensitive to the noun-verb contrast, but the vMMN was not.

Figure 3 here

Discussion

The current study investigated whether the contrast between words and pseudowords can generate vMMNs, as well as whether thecontrast between nouns and verbs can. The noun-verb contrast failed to elicit a vMMN. The cluster test for the lexicality contrast collapsed across conditions generated a borderline significant main effect (p=.051; while we acknowledge that this is not significant at the traditional alpha level, it is very close and suggestive of the fact that lexicality vMMNs may exist and may be discoverable in future studies using comparable stimuli). When broken down into separate conditions, we did not observe an effect for the pseudoword contrast, but the word contrast elicited a significant ERP in the form of a broadly distributed vMMN between 275ms to

400ms (although this potential difference was not supported by a significant interaction).

Previous studies examining visual word processing via the vMMN has found effects ranging from 100 to 400ms (Hu et al., 2020; Shtyrov et al., 2013; X. D. Wang et al., 2012; Wei et al., 2018). Our observed lexicality vMMN peaks at around 320ms, which is relatively late for a vMMN; this may be due to the high-level nature of the contrast in addition to the location of the critical contrast (last letter of each word). The primarily frontal distribution of the vMMN is rather typical, with multiple vMMN studies observing effects in the fronto-central area (Csukly et al., 2013; Stefanics et al., 2012; S. Wang et al., 2016).

The present study is the first, to our knowledge, to observe a vMMN (or any MMN) for an abstract word-pseudoword contrast. Several previous studies have observed that word deviants elicit larger MMNs than pseudoword deviants (see, e.g., Politzer-Ahles & Im, 2020, for review and critique of these findings), but these have always relied on MMNs cued by a low-level physical difference between the deviant and the standard. For example, Shtyrov and colleagues (2013) observed MMNs for the contrast between H and K, regardless of whether the standards and deviants were words or pseudowords. Thus, the effect they report is not an MMN driven by the difference between word and pseudoword, but an MMN driven by the difference between the letters H and K.In the present study, we eliminated clear physical differences which may be the source of the vMMN elicitation and presented a true lexicality contrast where the only systematic difference between the standard and deviant was whether it is a word or a pseudoword.

Our findings align with a predictive coding framework (Bornkessel-Schlesewsky & Schlesewsky, 2019; Stefanics et al., 2015), wherein the brain continuously updates its predictions about upcoming input at multiple levels of representation. When participants are exposed to a block that overwhelmingly features real words (or pseudowords), they form an implicit prediction about the lexical status of impending stimuli. Encountering a deviant category (e.g., a pseudoword unexpectedly presented amidst repeated word standards) produces a prediction error, manifesting as a stronger vMMN for items that violate the existing lexical-semantic expectation. In contrast, Shtyrov et al. (2013) observed ERP differences between words and pseudowords, but their design did not isolate a mismatch effect specific to these higher-level lexical representations. The current finding can address these limitations by demonstrating a vMMN specifically tied to lexical status, rather than just a general difference in ERP responses to words and pseudowords. The absence of a vMMN for pseudoword deviants supports predictive coding theory: robust lexical predictions are only formed for familiar words with pre-existing representations. Pseudowords, lacking such representations, cannot generate strong predictions to violate.

The vMMN observed in this study cannot be attributed to differences in physical, orthographic, phonological, lexical, or semantic properties between the deviant and critical standard stimuli. Although the stimuli sets included different "extra" standards, no predictive rule could be formed based on these properties. Participants cannot notice patterns like a prevalence of certain word endings as the distinction relied on recognizing contrasts in the frequency of words versus pseudowords. Moreover, the vMMN cannot be explained by variations in neural refractoriness between the event-related potentials elicited by deviants and control standards. This is because both stimulus types were presented with similar frequency (45 occurrences per block) within the oddball paradigm. Additionally, the repetition of some words across blocks (e.g., pakar, petir) does not confound the results. All stimuli were repeated frequently within blocks, rendering repetition effects negligible by the time they appear as critical trials. In addition, Naccache et al. (2002) provided evidence that unattended stimuli do not generate priming effects, even at short intervals. They demonstrated that when temporal attention is directed away from stimuli, both response-congruity and physical repetition priming vanish. Given these findings, *long-lag* priming effects from stimuli presented in previous blocks are extremely unlikely, particularly since our stimuli were presented as unattended standards with long intervals between blocks. Furthermore, the global imbalance in word vs. pseudoword frequency across the experiment does not explain the observed asymmetry in vMMN elicitation. If overall frequency were the primary driver, pseudoword deviants should elicit a stronger vMMN. Instead, we observed a vMMN only for word deviants, which were globally more frequent.

As such, alternative explanations for the observed vMMN should be considered. The mismatch negativity and its visual counterpart are typically interpreted as indicators of prediction error in the brain's processing of sensory information (Garrido et al., 2009; Weber et al., 2018). The human brain can generate predictions for upcoming visual events not only at the sensory level but also at higher cognitive levels (Stefanics et al., 2015). The findings suggest that semantic information from visual words can be rapidly processed without being indexed by attention, reflecting the implicit mechanisms underlying semantic processing of visual stimuli and confirming findings from previous studies (Shtyrov et al., 2013).

While the prediction error model is widely accepted, an alternative explanation for MMN/vMMN generation is the adaptation hypothesis (Gu et al., 2018). This theory proposes that MMN/vMMN arises from fundamental neurophysiological mechanisms in the cerebral cortex, such as adaptation and lateral inhibition (Gu et al., 2018; May & Tiitinen, 2010). According to this view, frequently presented standard stimuli lead to significant adaptation of neural ensembles responding to the semantic category information of these standards. In contrast, neural ensembles responding to the semantic category information of deviant stimuli are less adapted, resulting in the vMMN effect (Weber et al., 2018). However, it is crucial to recognize that while the adaptation hypothesis may contribute to various effects classified as MMNs, it does not fully account for all findings in the literature. Previous studies have shown that MMN can occur even when controlling for refractoriness effects, suggesting that the adaptation mechanism alone is insufficient to explain the phenomenon completely. For example, some previous MMN studies (e.g. Politzer-Ahles et al., 2016; Schröger & Wolff, 1996) have included a "control" block where tokens from each condition were presented with equal frequency with random order—meaning that each category was presented at a one out of seven (14.3%) ratio, approximately equal to the ratio of deviants to standards in normal blocks. Such studies still find an MMN, which cannot be accounted for as an artifact of N1 differences. What this literature demonstrates is that many results that look like MMNs actually consist of two separate but overlapping effects: a residual N1 (which is reduced in standards but not in deviants, and thus remains after the oddball subtraction procedure) and a "true" MMN. While many studies have failed to separate these, the ones that do have found that there is still a "true" MMN separate from the confounding N1 effect. And in the present study, there is no reason for the N1 to be different between deviants and standards (since standard stimuli were repeated no more often than deviant stimuli), and thus the effect we observed should be a “true” MMN, rather than a residual N1.

Regardless of the specific neural mechanisms underlying vMMN, the current results provide evidence for rapid semantic processing of visual words. The vMMN occurred early and with minimal attentional engagement which suggests that it may engage automatic or implicit processes (Qin et al., 2021; Stefanics et al., 2015).

While we did not observe a visual MMN in the word class contrast condition, it would be rather premature to conclude that higher-level processing such as recognizing word features do not occur automatically in the visual modality. It seems to be too early to tell: English speakers were able to subconsciously detect tense differences in spoken words (Politzer-Ahles & Jap, 2024), and while this is different from word class, both are abstract linguistic contrasts. We were not able to find evidence that abstract linguistic information such as the verb-noun contrast is processed automatically in the visual modality, but the findings extend previous evidence on automatic lexicality detection of stimuli. The inconsistent result on abstract linguistic processing could stem from unknown interactions ("hidden moderators") between the modality, materials, and perhaps even the language at hand, noting the complete lack of ERP research in Standard Indonesian. Finally, while our counterbalanced block order (two lists) controlled for sequencing biases, future studies with larger trial counts could investigate if block order could affect vMMN elicitation for abstract linguistic contrasts.

Acknowledgments

The authors would like to thank Wenxi Fei for her assistance during data collection for this study.

Declaration of interest statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Funding details

Stephen Politzer-Ahles, Hong Kong Research Grants Council General Research Fund, Award ID: 15605620.

Data availability statement

Data will be made available on reasonable request.

References

Astikainen, P., Kreegipuu, K., & Czigler, I. (2022). Editorial: Visual mismatch negativity (vMMN): A unique tool in investigating automatic processing. *Frontiers in Human Neuroscience*, *16*, 1056208. https://doi.org/10.3389/fnhum.2022.1056208

Bornkessel-Schlesewsky, I., & Schlesewsky, M. (2019). Toward a neurobiologically plausible model of language-related, negative event-related potentials. *Frontiers in Psychology*, *10*, 298.

Boudewyn, M. A., Luck, S. J., Farrens, J. L., & Kappenman, E. S. (2018). How Many Trials Does It Take to Get a Significant ERP Effect? It Depends. *Psychophysiology*, *55*(6), e13049. https://doi.org/10.1111/psyp.13049

Coch, D., & Mitra, P. (2010). Word and pseudoword superiority effects reflected in the ERP waveform. *Brain Research*, *1329*, 159–174. https://doi.org/10.1016/j.brainres.2010.02.084

Csukly, G., Stefanics, G., Komlósi, S., Czigler, I., & Czobor, P. (2013). Emotion-Related Visual Mismatch Responses in Schizophrenia: Impairments and Correlations with Emotion Recognition. *PLOS ONE*, *8*(10), e75444. https://doi.org/10.1371/journal.pone.0075444

Delorme, A. (2023). EEG is better left alone. *Scientific Reports*, *13*(1), 2372. https://doi.org/10.1038/s41598-023-27528-0

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*, *15;134(1):9-21*.

Eulitz, C., & Lahiri, A. (2004). Neurobiological evidence for abstract phonological representations in the mental lexicon during speech recognition. *Journal of Cognitive Neuroscience*, *16*, 577–583.

Friederici, A. D. (2002). Towards a neural basis of auditory sentence processing. *Trends in Cognitive Sciences*, *6*(2), 78–84. https://doi.org/10.1016/S1364-6613(00)01839-8

Garrido, M. I., Kilner, J. M., Stephan, K. E., & Friston, K. J. (2009). The mismatch negativity: A review of underlying mechanisms. *Clinical Neurophysiology*, *120*(3), 453–463. https://doi.org/10.1016/j.clinph.2008.11.029

Goldhahn, D., Eckart, T., & Quasthoff, U. (2012). *Building large monolingual dictionaries at the leipzig corpora collection: From 100 to 200 languages*. InProceedings of the Eighth International Conference on Language Resources and Evaluation (LREC-12) 2012 May.

Groppe, D. M., Urbach, T. P., & Kutas, M. (2011). Mass univariate analysis of event-related brain potentials/fields I: A critical tutorial review. *Psychophysiology*, *Dec;48(12):1711-25*.

Gu, F., Wong, L., Chen, F., Huang, W.-T., Wang, L., & Hu, A.-X. (2018). Lateral Inhibition is a Neural Mechanism Underlying Mismatch Negativity. *Neuroscience*, *385*, 38–46. https://doi.org/10.1016/j.neuroscience.2018.06.009

Hagoort, P. (2007). The fractionation of spoken language understanding by measuring electrical and magnetic brain signals. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *363*(1493), 1055–1069. https://doi.org/10.1098/rstb.2007.2159

He, T., Boudewyn, M. A., Kiat, J. E., Sagae, K., & Luck, S. J. (2022). Neural correlates of word representation vectors in natural language processing models: Evidence from representational similarity analysis of event-related brain potentials. *Psychophysiology*, *59*(3), e13976. https://doi.org/10.1111/psyp.13976

Hu, A., Gu, F., Wong, L., Tong, X., & Zhang, X. (2020). Visual mismatch negativity elicited by semantic violations in visual words. *Brain Research*, 147010.

Jap, B. A. J., Hsu, Y.-Y., & Politzer-Ahles, S. (2022). Neural correlates of thematic role assignment for passives in Standard Indonesian. *PLOS ONE*, *17*(8), e0272207. https://doi.org/10.1371/journal.pone.0272207

Kazanina, N., Phillips, C., & Idsardi, W. (2006). The influence of meaning on the perception of speech sounds. *Proceedings of the National Academy of Sciences of the United States of America*, *103*, 11381–11386.

Krauska, A., & Lau, E. (2023). Moving away from lexicalism in psycho- and neuro-linguistics. *Frontiers in Language Sciences*, *2*. https://doi.org/10.3389/flang.2023.1125127

Krivochen, D. G. (2014). At the Interface of (Bio)linguistics, Language Processing, and Neuropsychology. *Biolinguistics*, *8*, 141–162. https://doi.org/10.5964/bioling.9007

Li, N., Wang, S., Kornrumpf, F., Sommer, W., & Dimigen, O. (2024). Parafoveal and foveal N400 effects in natural reading: A timeline of semantic processing from fixation-related potentials. *Psychophysiology*, *61*(5), e14524. https://doi.org/10.1111/psyp.14524

Lu, S., Wayland, R., & Kaan, E. (2015). Effects of production training and perception training on lexical tone perception – A behavioral and ERP study. *Brain Research*, 28–44.

Makeig, S., Jung, T. P., Bell, A. J., Ghahremani, D., & Sejnowski, T. J. (1997). Blind separation of auditory event-related brain responses into independent components. *Proceedings of the National Academy of Sciences*, *30;94(20):10979-84*.

Male, A. G., O'Shea, R. P., Schröger, E., Müller, D., Roeber, U., & Widmann, A. (2020). The quest for the genuine visual mismatch negativity (vMMN): Event-related potential indications of deviance detection for low-level visual features. *Psychophysiology*, *57*(6), e13576. https://doi.org/10.1111/psyp.13576

Maris, E., & Oostenveld, R. (2007). Nonparametric statistical testing of EEG-and MEG-data. *Journal of neuroscience methods*, *15;164(1):177-90*.

May, P. J. C., & Tiitinen, H. (2010). Mismatch negativity (MMN), the deviance-elicited auditory deflection, explained. *Psychophysiology*, *47*(1), 66–122. https://doi.org/10.1111/j.1469-8986.2009.00856.x

Näätänen, R., Paavilainen, P., Rinne, T., & Alho, K. (2007). The mismatch negativity (MMN) in basic research of central auditory processing: A review. *Clinical Neurophysiology*, *118*(12), 2544–2590. https://doi.org/10.1016/j.clinph.2007.04.026

Naccache, L., Blandin, E., & Dehaene, S. (2002). Unconscious Masked Priming Depends on Temporal Attention. *Psychological Science*, *13*(5), 416–424. https://doi.org/10.1111/1467-9280.00474

O'Connor, K. (2012). Auditory processing in autism spectrum disorder: A review. *Neuroscience and Biobehavioral Reviews*, *36*, 836–854.

Oostenveld, R., Fries, P., Maris, E., & Schoffelen, J. M. (2011). FieldTrip: Open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data. *Computational Intelligence and Neuroscience*.

Petro, B., Gaál, Z. A., Kojouharova, P., & Czigler, I. (2023). The role of attention control in visual mismatch negativity (vMMN) studies. *Experimental Brain Research*, *241*(4), 1001–1008. https://doi.org/10.1007/s00221-023-06573-1

Phillips, C., Pellathy, T., Marantz, A., Yellin, E., Wexler, K., Poeppel, D., McGinnis, M., & Roberts, T. (2000). Auditory cortex accesses phonological categories: An MEG mismatch study. *Journal of Cognitive Neuroscience*, *12*, 1038–1055.

Pion-Tonachini, L., Kreutz-Delgado, K., & Makeig, S. (2019a). ICLabel: An automated electroencephalographic independent component classifier, dataset, and website. *NeuroImage*, *198*, 181–197. https://doi.org/10.1016/j.neuroimage.2019.05.026

Pion-Tonachini, L., Kreutz-Delgado, K., & Makeig, S. (2019b). The ICLabel dataset of electroencephalographic (EEG) independent component (IC) features. *Data in Brief*, *25*, 104101. https://doi.org/10.1016/j.dib.2019.104101

Politzer-Ahles, S., & Jap, B. A. J. (2024). Can the Mismatch Negativity Really Be Elicited by Abstract Linguistic Contrasts? *Neurobiology of Language*, *5*(4), 818–843. https://doi.org/10.1162/nol_a_00147

Politzer-Ahles, S., Schluter, S., Wu, K., & Almeida, D. (2016). Asymmetries in the perception of Mandarin tones: Evidence from mismatch negativity. *Journal of Experimental Psychology: Human Perception and Performance*, *42*, 1547–1570.

Pulvermüller, F., Shtyrov, Y., & Hauk, O. (2009). Understanding in an instant: Neurophysiological evidence for mechanistic language circuits in the brain. *Brain and Language*, *110*(2), 81–94. https://doi.org/10.1016/j.bandl.2008.12.001

Schall, U. (2016). Is it time to move mismatch negativity into the clinic? *Biological Psychology*, *116*, 41–46.

Schröger, E., & Wolff, C. (1996). Mismatch response of the human brain to changes in sound location. *NeuroReport*, *7*(18), 3005.

Shtyrov, Y., Goryainova, G., Tugin, S., Ossadtchi, A., & Shestakova, A. (2013). Automatic processing of unattended lexical information in visual oddball presentation: Neurophysiological evidence. *Frontiers in Human Neuroscience*, *7*. https://doi.org/10.3389/fnhum.2013.00421

Shtyrov, Y., Osswald, K., & Pulvermüller, F. (2008). Memory Traces for Spoken Words in the Brain as Revealed by the Hemodynamic Correlate of the Mismatch Negativity. *Cerebral Cortex*, *18*(1), 29–37. https://doi.org/10.1093/cercor/bhm028

Smulders, F., & Miller, J. (2012). The lateralized readiness potential. In S. Luck & E. Kappeman (Eds.), *The Oxford handbook of event-related potential components*.

Stefanics, G., Astikainen, P., & Czigler, I. (2015). Visual mismatch negativity (vMMN): A prediction error signal in the visual modality. *Frontiers in Human Neuroscience*, *8*, 1074. https://doi.org/10.3389/fnhum.2014.01074

Stefanics, G., Csukly, G., Komlósi, S., Czobor, P., & Czigler, I. (2012). Processing of unattended facial emotions: A visual mismatch negativity study. *NeuroImage*, *59*(3), 3042–3049. https://doi.org/10.1016/j.neuroimage.2011.10.041

Stefanics, G., Kremláček, J., & Czigler, I. (2014). Visual mismatch negativity: A predictive coding view. *Frontiers in Human Neuroscience*, *8*. https://doi.org/10.3389/fnhum.2014.00666

Wang, S., Li, W., Lv, B., Chen, X., Liu, Y., & Jiang, Z. (2016). ERP comparison study of face gender and expression processing in unattended condition. *Neuroscience Letters*, *618*, 39–44. https://doi.org/10.1016/j.neulet.2016.02.039

Wang, X. D., Gu, F., He, K., Chen, L. H., & Chen, L. (2012). Preattentive extraction of abstract auditory rules in speech sound stream: A mismatch negativity study using lexical tones. *PLoS ONE*, *7*, 30027.

Weber, L., Diaconescu, A., Tomiello, S., Schöbi, D., Iglesias, S., Mathys, C., Haker, H., Stefanics, G., Schmidt, A., Kometer, M., Vollenweider, F. X., & Stephan, K. E. (2018). F157. HIERARCHICAL PREDICTION ERRORS DURING AUDITORY MISMATCH UNDER PHARMACOLOGICAL MANIPULATIONS: A COMPUTATIONAL SINGLE-TRIAL EEG ANALYSIS. *Schizophrenia Bulletin*, *44*(Suppl 1), S281–S282. https://doi.org/10.1093/schbul/sby017.688

Wei, D., Gillon Dowens, M., & Guo, T. (2018). Early lexical processing of Chinese words indexed by Visual Mismatch Negativity effects. *Scientific Reports*, *8*(1), 1289. https://doi.org/10.1038/s41598-018-19394-y

Winkler, I. (2007). Interpreting the mismatch negativity. *Journal of Psychophysiology*, *21*, 147–163.

Winkler, I., & Czigler, I. (2012). Evidence from auditory and visual event-related potential (ERP) studies of deviance detection (MMN and vMMN) linking predictive coding theories and perceptual object representations. *International Journal of Psychophysiology*, *83*(2), 132–143. https://doi.org/10.1016/j.ijpsycho.2011.10.001

Yudes, C., Domínguez, A., Cuetos, F., & de Vega, M. (2016). The time-course of processing of grammatical class and semantic attributes of words: Dissociation by means of ERP. *Psicológica*, *37*(2), 105–126.

Zarza, D., Arce-Arce, S., Bhathal, H., & Sanjuán-Martín, F. (2007). Mismatch negativity and conscience level in severe traumatic brain injury. *Revista de neurologia*, *44*, 465–468.

Table 1. Word list for experiment.

Block Type: **Deviant Type:**	Word class Verb	Word class Noun	Type Word	Type Pseudoword
Critical deviants	**pakai** **bakar** **tarik**	**pakar** **bakat** **tarif**	**pakai** **bakar** **tarik**	**pakas** **bakan** **tarit**
Critical standards	**pakar** **bakat** **tarif**	**pakai** **bakar** **tarik**	**pakas** **bakan** **tarit**	**pakai** **bakar** **tarik**
Extra standards	perak petir bahan bayam taman tanah gagak gugus makam	peras petik bahas bayar tamat tanam gagal gugur makan	pakak petim bahap bakas taril tanan gagat gugum makak	pakar petir bahan bakat tarif tanah gagal gugur makan

Table 2. Frequencies for the critical deviants and critical standards for the word class and lexicality contrast blocks

	Frequency class*	Frequency tokens
pakai	8	129209
bakar	8	124105
tarik	9	51885
pakar	9	50900
bakat	10	33649
tarif	9	83588

* Frequency class is a standardized number assigned to a group of words to allow comparison across different corpora. The calculation is as follows: The frequency of the most frequent word in the corpus is divided by the frequency of the specific word, and log base 2 of the result is rounded up to the closest whole number (Jap et al., 2022).

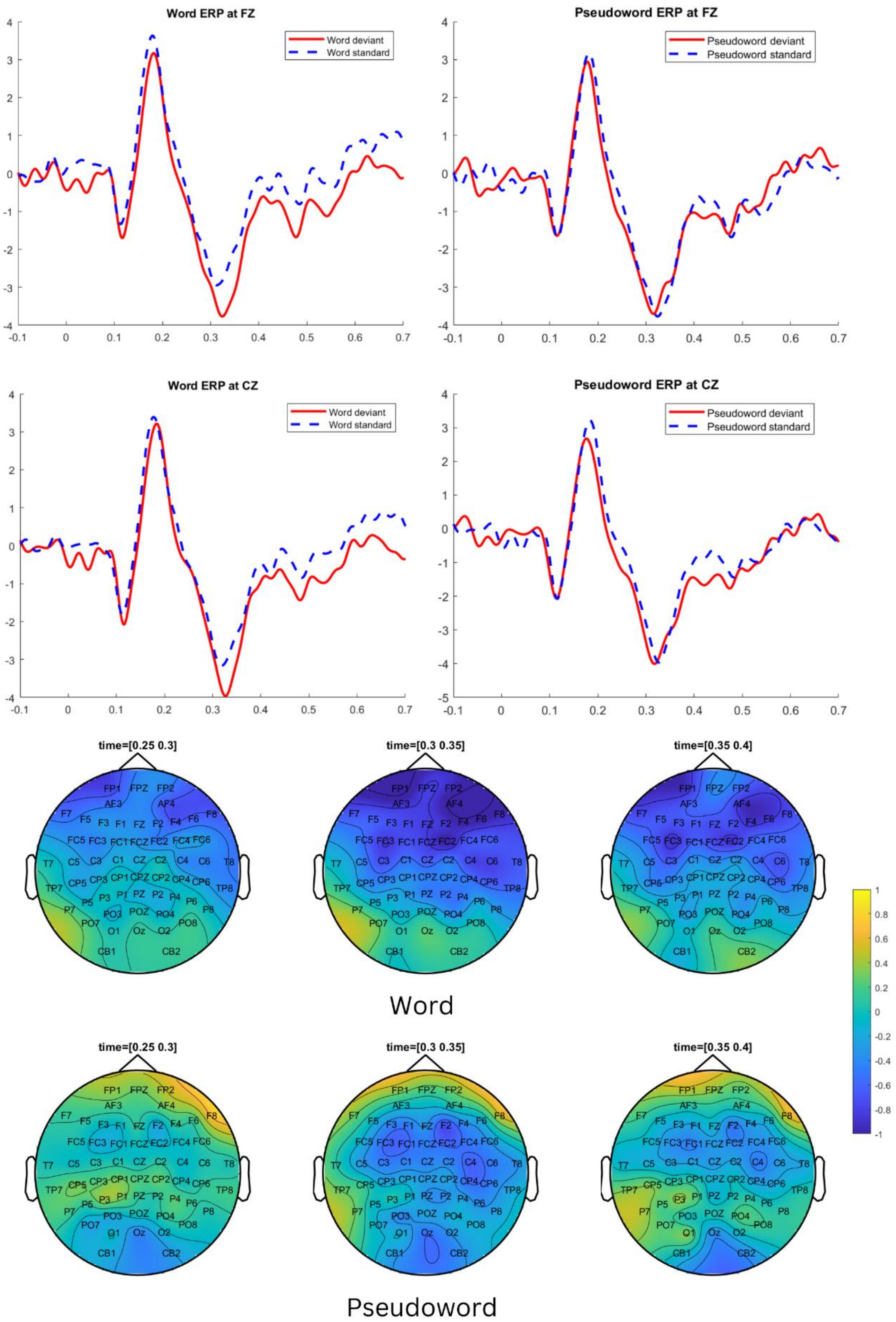
Word ERP at FZ
Word deviant
Word standard
Pseudoword ERP at FZ
Pseudoword deviant
Pseudoword standard
Word ERP at CZ
Word deviant
Word standard
Pseudoword ERP at CZ
Pseudoword deviant
Pseudoword standard
time=[0.25 0.3]
time=[0.3 0.35]
time=[0.35 0.4]
Word
time=[0.25 0.3]
time=[0.3 0.35]
time=[0.35 0.4]
Pseudoword

Figure 1.

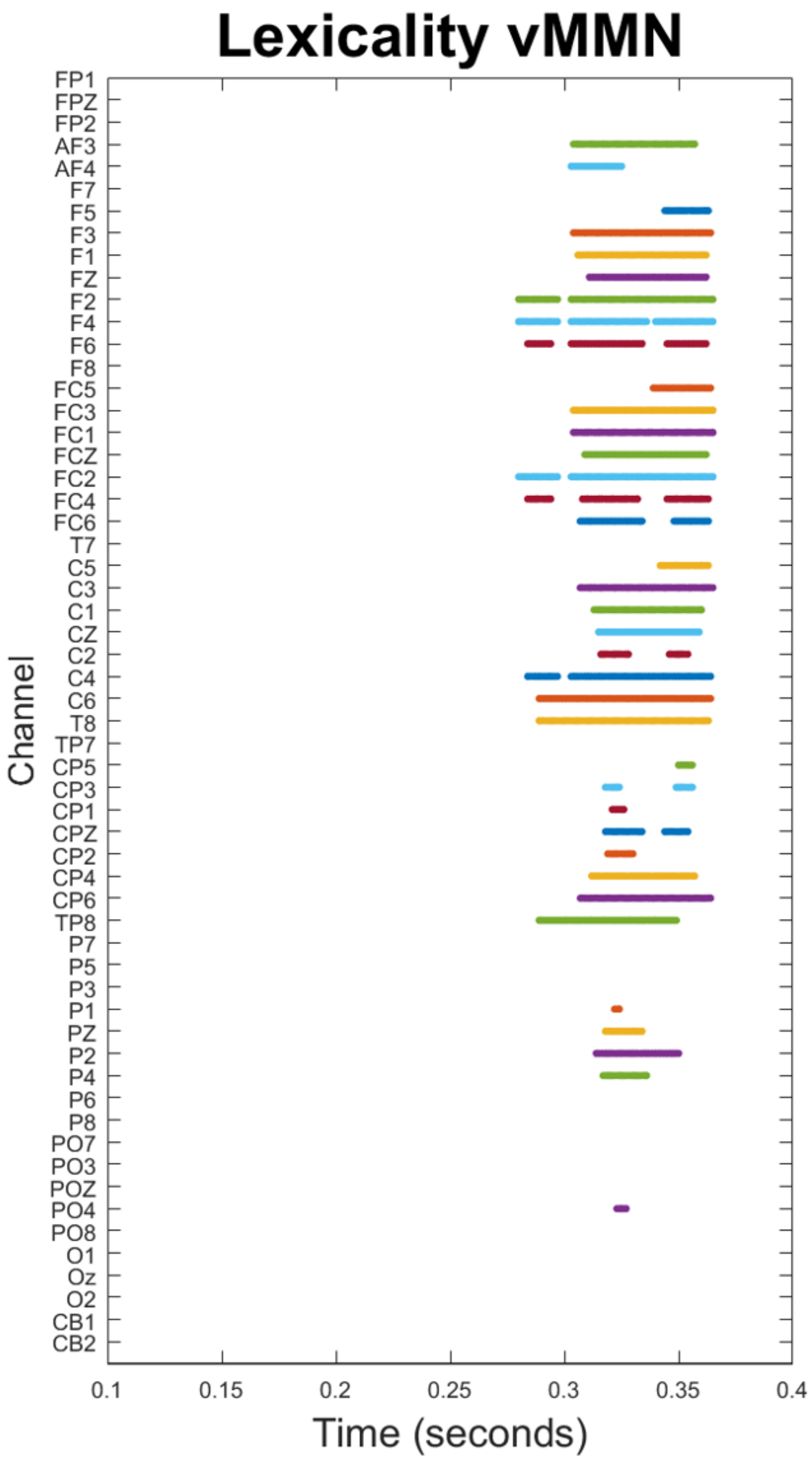
Lexicality vMMN
FP1
FPZ
FP2
AF3
AF4
F7
F5
F3
F1
FZ
F2
F4
F6
F8
FC5
FC3
FC1
FCZ
FC2
FC4
FC6
T7
C5
C3
C1
CZ
C2
C4
C6
T8
TP7
CP5
CP3
CP1
CPZ
CP2
CP4
CP6
TP8
P7
P5
P3
P1
PZ
P2
P4
P6
P8
PO7
PO3
POZ
PO4
PO8
O1
Oz
O2
CB1
CB2
Channel
0.1
0.15
0.2
0.25
0.3
0.35
0.4
Time (seconds)

Figure 2.

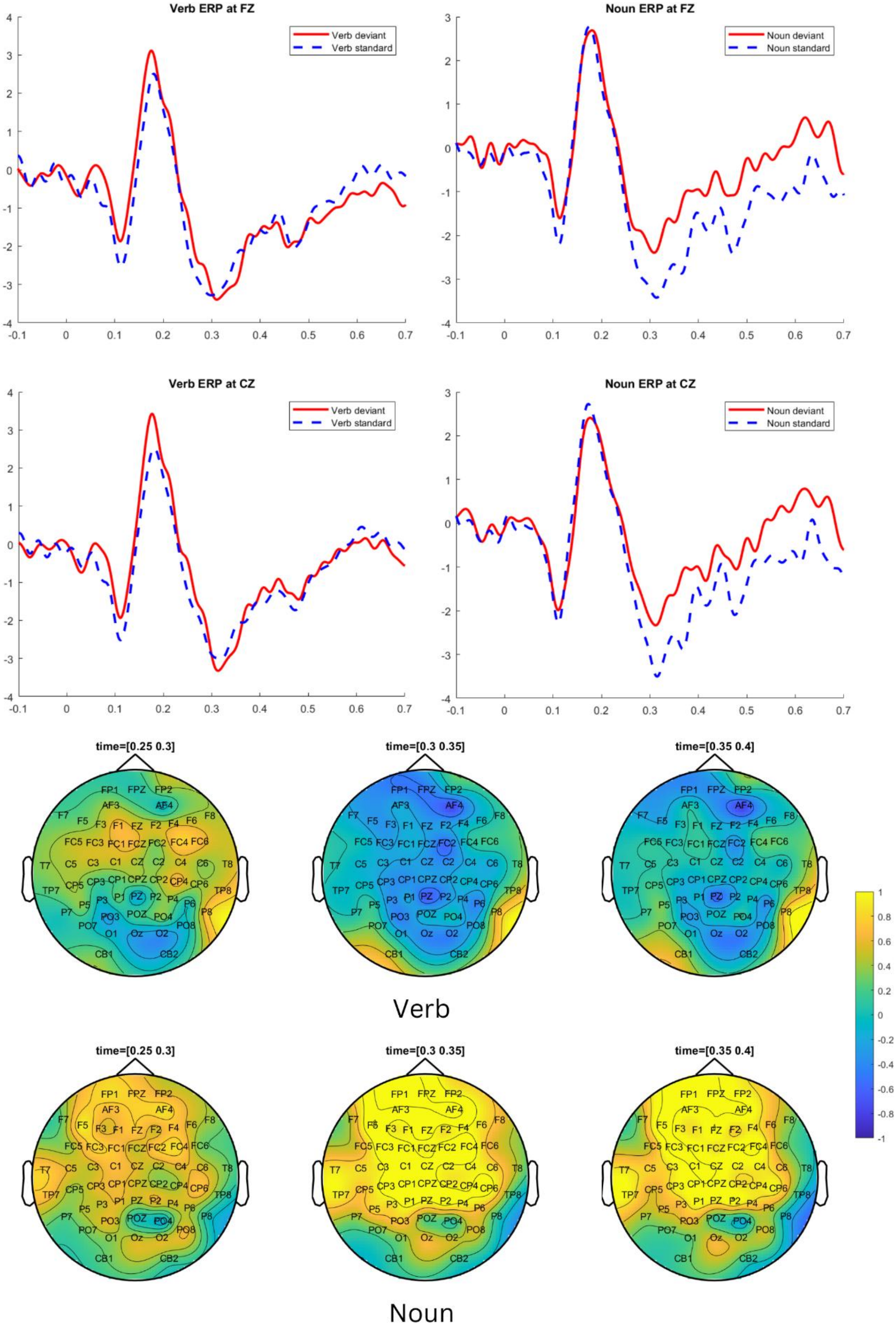
Verb ERP at FZ
Verb deviant
Verb standard
Noun ERP at FZ
Noun deviant
Noun standard
Verb ERP at CZ
Verb deviant
Verb standard
Noun ERP at CZ
Noun deviant
Noun standard
time=[0.25 0.3]
time=[0.3 0.35]
time=[0.35 0.4]
Verb
Noun

Figure 3.

Figure captions

Figure 1. ERPs for lexicality contrast at two representative channels (FZ & CZ) and topographic difference plots (deviant minus standard) showing ERPs for the 250 to 400 ms time window; scale is from -1 to 1 μV.

Figure 2. Raster plot showing which data points (i.e., which electrodes at which time points) were included in the cluster permutation-tested for the lexicality contrast collapsed across conditions.

Figure 3. ERPs for word class contrast at two representative channels (FZ & CZ) and topographic difference plots (deviant minus standard) for the 250 to 400 ms time window; scale is from -1 to 1 μV.