Exploring neural tracking of acoustic and linguistic speech representations in individuals with post-stroke aphasia

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Abstract

Aphasia is a communication disorder that affects processing of language at different levels (e.g., acoustic, phonological, semantic). Neural tracking of continuous speech, such as a story, allows to analyze brain responses to acoustic and linguistic properties. Even though neural tracking of speech measured via EEG may be an interesting tool to study aphasia in an ecologically valid way, this method has not yet been investigated in individuals with stroke-induced aphasia. Here, we explored processing of acoustic and linguistic speech representations in individuals with aphasia in the chronic phase after stroke and age-matched healthy controls. We found decreased neural tracking of acoustic and segmentation-related speech representations in individuals with aphasia. In addition, linguistic speech representations at the word-level displayed decreased amplitudes in individuals with aphasia around 200 ms over left-sided frontal electrodes. These results show that there is potential for neural tracking to capture language processing impairments in individuals with aphasia. However, more research is needed to validate these results. Nonetheless, this exploratory study shows that neural tracking of naturalistic, continuous speech presents a powerful tool to study aphasia.

1 Introduction

About one third of strokes result in aphasia, a language disorder that can impact auditory comprehension, oral production, writing and/or reading (Engelter et al., 2006; National Aphasia Association, 2022; Pasley and Knight, 2013). Aphasia can impact communication to different degrees, ranging from subtle to severe impairments, and from recovery within hours after stroke to permanent language impairments. The severity and persistence depend on factors such as lesion location and size, brain plasticity, therapy, intrinsic motivation and social support (Pasley and Knight, 2013; Schevenels et al., 2020; Cordella et al., 2022; Schevenels et al., 2022). In order to be effective, speech therapy should be given with high intensity and the content should be tailored to the specific problems of each individual with aphasia (IWA) (Rohde et al., 2018; Engelter et al., 2006; Schevenels et al., 2020; Brady, 2022). Individually tailored therapy requires a precise diagnosis of language impairments.

Although diagnostic tests originally focused on the classic aphasia typology (i.e., assessing performance on fluency, comprehension and repetition tasks), neuroimaging studies have suggested that focusing on the different language processing components (i.e., acoustic, phonological, semantic, syntactic) is more in line with the neural networks of language processing (Rohde et al., 2018; Tremblay and Dick, 2016; Pasley and Knight, 2013). Hence, a neuroimaging approach focused on the linguistic aspects may yield more precise diagnostic insights and a more effective therapeutic approach (Tremblay and Dick, 2016; Pasley and Knight, 2013). Moreover, behavioral testing after stroke is difficult because in 80% of cases, IWA one year post-stroke have co-morbid cognitive problems, such as memory, executive functions and/or attention problems, which can bias the results or even impede behavioral testing (El Hachioui et al., 2014; Fonseca et al., 2018). Further, behavioral tests consist of artificial tasks that do not always correspond to communication abilities in daily life. Thus, to provide targeted intervention and improve recovery outcomes, an aphasia diagnosis that provides precise insights, that is less dependent on cognitive performance and that is more ecologically valid is needed.

Electroencephalography (EEG) provides ways to study the brain's responses to speech with reduced active participation of the patient. By averaging the EEG signal in response to a large number of repetitive sound or speech stimuli, peaks in specific time ranges have been consistently identified in neurotypicals, i.e., event-related potentials (ERPs), offering a window into the spatio-temporal patterns of the neural response to speech. This way, ERPs related to acoustic (e.g., P1-N1-P2 complex (e.g., Martin et al., 2008; Harris, 2020)) and linguistic (e.g., N400 (e.g., Hillyard and Kutas, 1984; Kutas and Federmeier, 2011; Nieuwland et al., 2020)) aspects of speech have been identified. In IWA, altered ERPs have been found across language processing levels and across a variety of experimental stimuli and tasks (Ofek et al., 2013; Becker and Reinvang, 2007; Ilvonen et al., 2001; Pulvermüller et al., 2004; Aerts et al., 2015; Ilvonen et al., 2004; Pettigrew et al., 2005; Robson et al., 2017; Chang et al., 2016; Kawohl et al., 2010;

Khachatryan et al., 2017; Sheppard et al., 2017; Lice and Palmović, 2017; Kielar et al., 2012; Räling et al., 2016). Most of these studies have reported decreased amplitudes and increased latencies in IWA as compared to healthy controls, with the exception of the P2 in Aerts et al. (2015) and Ilvonen et al. (2001), which observed opposite patterns. Some of these studies have found ERP amplitudes or latencies to be correlated with language performance (Pettigrew et al., 2005; Robson et al., 2017; Khachatryan et al., 2017).

The potential of ERPs to serve as evaluatory measure of intervention effects has recently been reviewed by Cocquyt et al. (2020), who concluded that there is potential for ERPs to assess levels of aphasia symptoms, after development of normative data. However, to date ERPs are not commonly used in the clinic. This is likely due to small sample sizes and the heterogeneity of aphasia symptoms within the studied samples (Silkes and Anjum, 2021), which complicates the development of validated norms for ERPs. While ERPs are useful to understand the functional meaning of different peaks in the spatio-temporal patterns of the neural response, their application in aphasia diagnostics poses further challenges, e.g., long administration time due to different paradigms at distinct speech processing levels and the need for a large number of repetitive stimuli to average across (Kandylaki and Bornkessel-Schlesewsky, 2019). Moreover, listening to repetitive and artificially created stimuli is not representative of everyday language situations that IWA struggle with mostly (Le et al., 2018). More naturalistic speech stimuli, such as a narrative, would present a more ecologically valid stimulus to analyze the brain's response to speech (Lalor and Foxe, 2010; Ding and Simon, 2012; Hamilton and Huth, 2018; Kandylaki and Bornkessel-Schlesewsky, 2019; Gillis et al., 2022).

From the narrative, different characteristics or representations of speech can be derived and their relation to the EEG signal can be measured, a method called neural tracking. This way, spatial and temporal neural response properties in response to multiple speech representation levels (e.g., acoustic, phonological, semantic, syntactic) can be analyzed from the same data (Di Liberto et al., 2015; Brodbeck et al., 2018; Gillis et al., 2021, 2022; Mesik et al., 2021). Moreover, this method provides a measure of the strength with which the different speech representations are encoded in the EEG signal. Research has shown that even relatively short EEG recordings (i.e., 10-20 minutes) can provide valid results with this approach (Di Liberto and Lalor, 2017). Furthermore, limited active participation is required from the participant during such a paradigm, which is especially advantageous for testing IWA. These characteristics make neural tracking an ideal tool to study aphasia.

Using neural tracking, the most frequently studied speech representation to date is the speech envelope, consisting of the slow amplitude modulations of speech over time (Aiken and Picton, 2008). The envelope presents an essential cue for speech intelligibility (Aiken and Picton, 2008; Shannon et al., 1995). Whereas envelope tracking has not yet been investigated in individuals with stroke-induced aphasia, Dial et al.

(2021) have explored it in individuals with primary progressive aphasia (PPA). Individuals with the logopenic variant of this neurodegenerative disease displayed increased envelope tracking compared to healthy controls in the delta and theta band (Dial et al., 2021). On the other hand, envelope tracking in other disorders, such as developmental dyslexia, have shown decreased envelope tracking compared to controls (Di Liberto and Lalor, 2017). These studies show that neural tracking of continuous speech presents a promising new avenue to study language disorders.

While envelope tracking is mostly considered an acoustic process in the literature, it has been found to be affected by speech intelligibility and higher-level speech-specific processes (Peelle et al., 2013; Vanthornhout et al., 2018; Broderick et al., 2019; Prinsloo and Lalor, 2022). This is not surprising given that the speech envelope also encompasses important cues for segmentation (i.e., rise and fall times to identify acoustic edges) of the continuous speech signal into discrete units (i.e., phonemes, syllables, words, phrases) (Aiken and Picton, 2008). Moreover, the syllable stress is also comprised in the envelope, which gives the listener an indication of the prosody and thus even conveys linguistic information. Given this entanglement of acoustic and linguistic cues, the speech envelope alone may not be ideal to find specific neurophysiological correlates of acoustic, phonological and lexical semantic processing in aphasia.

Recently, higher-level linguistic speech representations have been investigated using neural tracking, i.e., speech representations containing information about phonemes and words that take into account linguistic context (Broderick et al., 2018; Brodbeck et al., 2018; Weissbart et al., 2019; Gillis et al., 2021). This way, it has been observed that older adults, in comparison to younger adults, have an altered neural response to linguistic processes (Broderick et al., 2021; Mesik et al., 2021; Gillis and Kries et al., 2023). To date, higher-level linguistic speech representations have not been investigated in IWA via neural tracking, although higher-level speech processing impairments at the phonological and semantic level are reported most frequently in IWA (in contrast to acoustic processing impairments).

In the present study, we investigated neural tracking of acoustic and linguistic speech representations in individuals with post-stroke aphasia and healthy, age-matched controls. To this end, EEG data was acquired while participants listened to a continuous story, of which 8 speech representations were derived. The envelope and envelope onsets were considered to be acoustic representations of speech, as we controlled the variance explained by linguistic information. The phoneme and word onsets were considered representations of speech segmentation, i.e., at the interface between acoustic and linguistic information. Lastly, phoneme surprisal and phoneme entropy were considered to be linguistic representations at the phoneme level, while word surprisal and word frequency were regarded as linguistic representations at the word level, i.e., related to lexical meaning. For the linguistic speech representations, we also controlled the variance explained by acoustic cues, as we aimed to disentangle different levels of speech processing. Ultimately, disentangling mechanisms at different levels of speech processing is necessary to investigate

whether neural tracking will be useful as a diagnostic tool for aphasia that provides information about different speech processing aspects. Here, our aim as a first step towards this goal was to explore group differences between IWA and healthy controls based on neural tracking of the different speech representations. Specifically, we studied group differences regarding the level of neural tracking, i.e., *how well* the brain tracks specific aspects of speech, and regarding *how* the spatio-temporal pattern of the neural response operates during continuous speech perception. Based on the aforementioned ERP and neural tracking studies, we expected to observe group differences in speech representations at both acoustic and linguistic levels.

2 Methods

2.1 Participants

We tested 41 IWA in the chronic phase after stroke ($\geq$ 6 months) and 24 healthy controls that were age-matched at group-level. IWA were recruited in two ways. Between October 2018 and April 2022 (with a COVID-19-related break between March and June 2020), patients were recruited via daily screening at the stroke unit of the university hospital Leuven (score $\leq$ cut-off threshold on the Language Screening Test (LAST) (Flamand-Roze et al., 2011)) or via advertising the study in speech-language pathologists' practices and rehabilitation centra (patients with a formal aphasia diagnosis) (see supplementary fig. S.1 for a detailed flowchart). Healthy age-matched controls were recruited via flyers positioned in recreational community centers for elderly. The target age of healthy controls was gradually adapted based on the mean age of IWA included in the study (supplementary figure S.2). The participants in this study are partly overlapping with participants in Kries et al. (2022, biorxiv).

For data collection, we only included IWA that had no formal diagnosis of a psychiatric or neurodegenerative disorder and that had a left-hemispheric or bilateral lesion. All aphasia participants were tested in the chronic phase after stroke (time since stroke onset in months (median(range)): 17.2(6-368.6)). The aphasia sample was checked for language impairments at the moment of data collection using two standardized diagnostic aphasia tests, i.e., the diagnostic test ScreeLing Visch-Brink et al. (2010) and the Dutch picture-naming test (Nederlandse Benoemtest (NBT); Van Ewijk et al. (2020), using the same procedure as reported in Kries et al. (2022, biorxiv). The ScreeLing was administered on a tablet using the Gorilla Experiment Builder (`http://www.gorilla.sc`) (Anwyl-Irvine et al., 2020). The average score by group is reported in table 1. We included individuals that scored either (1) below the cut-off threshold (ScreeLing threshold: 68/72 points; NBT threshold: 255/276 points) on at least one of these two tests at the moment of data collection (n=29) (table S.1; fig. S.3), or (2) had a documented language impairment in the acute phase (n=12). Note that 10 out of the latter 12 IWA still followed speech-language therapy at the time of data collection (table S.1).

All participants were Dutch native speakers from Flanders, Belgium. Informed consent was obtained from all participants for the recruitment via screening and for the data collection in the chronic phase. The study received ethical approval by the medical ethical committee of KU Leuven and UZ Leuven (S60007) and is in accordance with the declaration of Helsinki.

In table 1, we summarized demographic information by group (details can be found in table S.1). Age, sex, education, handedness and multilinguality did not differ between groups (age: W = 489.5, p = 0.978; sex: χ^2 = 0, df = 1, p = 1; education: χ^2 = 8.306, df = 4, p = 0.08; handedness: χ^2 = 0.036, df = 2, p = 0.981; multilingual: χ^2 = 0.126, df = 1, p = 0.722). Details about the stroke in IWA, i.e.,

time since stroke onset, stroke type, occluded blood vessel, lesion location and speech-language therapy, can be found in supplementary table S.1. Demographic information was acquired via a self-reported questionnaire. Handedness was assessed via the Edinburgh Handedness Inventory (Oldfield, 1971).

Table 1: Demographics, language-diagnostic information and covariates by group.

		Control	**Aphasia**	
Demographics				
Age in years (mean(SD))$^{\diamond}$		71.5(7)	69.8(12.6)	n.s.
Sex (n(%))	female	8(33.3%)	14(34.1%)	n.s.
	male	16(66.7%)	27(65.9%)	
Education (n(%))	primary education	0(0%)	4(9.7%)	n.s.
	secondary education	5(20.8%)	16(39%)	
	tertiary education/college	8(33.3%)	10(24.4%)	
	Master's degree	9(37.5%)	11(26.8%)	
	PhD	2(8.3%)	0(0%)	
Handedness (n(%))	right	22(91.6%)	37(90.2%)	n.s.
	left	1(4.2%)	2(4.9%)	
	ambidextrous	1(4.2%)	2(4.9%)	
Multilingual (n(%))	yes	22(91.7%)	35(85.4%)	n.s.
	no	2(8.3%)	6(14.6%)	
Language diagnostic tests				
ScreeLing (max=72) (mean(SD))		69.9(2.5)	61.6(9.2)	$***$
Picture naming (max=276) (mean(SD))		271.3(4.1)	226.4(57.1)	$***$
Covariates				
Hearing (Fletcher index in dB HL) (mean(SD))		24.5(12)	28.4(14.3)	n.s.
Cognition (OCS composite score in %) (mean(SD))		94.2(4.7)	79.8(16.5)	$***$
Alertness (Likert scale) (median(range))		4.75(3.5-5)	3.5(2-5)	$**$
Fatigue (Likert scale) (median(range))		1.5(1-4.5)	3.5(1-4.5)	$***$

$^{\diamond}$ Age is also used as a covariate; n.s. = not significantly different; $p<0.05^{*}$; $p<0.01^{**}$; $p<0.001^{***}$

2.2 Behavioral measures that serve as covariates

2.2.1 Hearing

Hearing thresholds were assessed via pure tone audiometry (PTA) at frequencies ranging from 0.25 to 4 kHz. In case the hearing thresholds below 4 kHz were >25 dB HL, this information was used to increase the amplitude of stimulus presentation during the EEG measurement. The PTA thresholds at 0.25, 0.5 and 1 kHz were averaged and then divided in half to come to the amount of dB that was added to the stimulus presentation amplitude of 60 dB SPL during the EEG paradigm. This calculation was done for each ear separately. After a short example stimulus, participants were asked whether the loudness was comfortable and if necessary the presentation volume was adjusted. Furthermore, hearing thresholds were used as covariates in statistical models (section 2.4). For this purpose, the Fletcher index (average of hearing thresholds at 0.5, 1 and 2 kHz) was calculated per ear and subsequently averaged across both ears. The Fletcher index did not differ between IWA and healthy controls ($W = 567$, $p = 0.311$, confidence interval: [-2.499 10.016]; table 1).

2.2.2 Cognition

The Oxford Cognitive Screen-NL was administered to assess cognitive functioning (Huygelier et al., 2019). This test was designed to be language-independent, such that cognitive functioning can be disentangled from language functioning, which is especially important for IWA. Due to limited time in the testing protocol, we chose to only assess 4/10 subscales, i.e. attention and hemispatial neglect, reading, executive functioning, and memory. Hemispatial neglect was used as a means to potentially exclude participants in case they had too severe hemineglect, which could bias outcomes at most of the administered tests. However, the highest hemineglect score was still at a very mild level and thus we decided to not exclude any participants based on hemispatial neglect.

The task to assess attention consisted of crossing out target shapes among distractor shapes. The task to assess executive functions consisted of connecting circles and triangles in alternation in descending order of size. The memory task consisted of free recall and recognition of words (from the sentence read for the reading task) and shapes. These 3 tasks were used to calculate a composite score of cognitive functioning. This score was calculated by transforming the raw scores of each test into percentages and then averaging across the three outcomes. The composite score was used to regress out differences in cognitive functioning to explore neural tracking differences between groups. The cognition composite score was significantly lower in IWA than in healthy controls ($W = 209.5$, $p < 0.001$).

2.2.3 Alertness and fatigue

Given that the experimental protocol (behavioral and EEG testing) was relatively long, especially considering that IWA often have cognitive impairments (e.g., attention), we decided to monitor the alertness and tiredness or fatigue at 3 time points throughout the experimental protocol (referred to as t1, t2 and t3). In supplementary figure S.4 E, the experimental protocol with reference to the timing of the alertness and fatigue questions is visualized. t1 was administered right at the start of the testing session, t2 after the EEG measurement and t3 at the end of the experimental protocol. Participants had to indicate on a Likert scale of 1 to 5 how alert and how tired they were at that moment. The questions were presented visually and auditory at the same time, as visualized in supplementary figure S.4 A and B. In supplementary section S.4, we describe the results of the interaction analysis between group and time points (fig. S.4 C and D, section S.1.1.4). Given that neural tracking has been shown to be influenced by attention (Lesenfants and Francart, 2020), we used the average ratings of t1 and t2 of the alertness and fatigue scale respectively as covariates in the analysis concerning group differences in neural tracking of speech. The average of t1 and t2 scores was specifically used because the EEG measurement took place in between these moments. A group difference was found for alertness ($W = 249.5$, $p = 0.001$) and for fatigue ($W = 210$, $p < 0.001$). IWA were on average less alert and more tired than healthy controls at t1 and t2 combined.

2.3 EEG-based measures

2.3.1 Experimental paradigm

The EEG measurements took place in a soundproof room with Faraday cage. We recorded 64-channel EEG (ActiveTwo, BioSemi, Amsterdam, NL) at a sampling frequency of 8192 Hz. Participants were instructed to listen to a 24 minute long story while EEG data was recorded. They were seated one meter away from a screen and were asked to look at a fixation cross while listening in order to minimize eye movement artifacts in the EEG signal (fig. 1 A). The story *De wilde zwanen* (The Wild Swans), written by Hans Christian Andersen and narrated by a female Flemish-native speaker, was cut into 5 parts of on average 4.84 minutes (standard deviation (SD): 9.58 seconds) each. The silences in the story were reduced to 200 ms duration and the sample rate was set to 48 kHz. The software APEX (Francart et al., 2008) was used to calibrate and present stimuli. The story was presented bilaterally via shielded ER-3A insert earphones (Etymotic Research) at an amplitude of 60 dB SPL (A weighted), except if hearing thresholds were above 25 dB HL at the PTA, in which case the presentation volume was augmented (see section 2.2.1).

After each story part, participants answered a yes/no question and a multiple choice question about the content of the preceding story part. As these questions were not validated, we did not assess them. They were solely introduced in the protocol to make participants follow the content of the story attentively. Nonetheless, 5 participants (4 IWA, 1 control) fell asleep during parts of the EEG measurement. Given that an awake state is necessary to follow the contents of a story (such as reflected in linguistic speech representations) (Makov et al., 2017), we decided to exclude these story parts from the analysis. For one other control participant, a part of the data was not saved correctly and could thus also not be used for analysis. This means that for 6 participants, less than 24 minutes of data was used for analysis (19.36 minutes of data for 1 control and 1 aphasia participant, 14.52 minutes for 1 control and 2 aphasia participants, 9.68 minutes for 1 aphasia participant).

2.3.2 EEG signal processing

The EEG signal processing was performed in MATLAB (version 9.1.0.441655 (R2016b)). The EEG data of the 5 story parts (i.e., epochs) were concatenated. Eye movement artifact removal was implemented using a multichannel Wiener filter (Somers et al., 2018). The EEG signal was referenced to the common average. For high-pass filtering, a least squares filter was applied with a filter order of 2000, with a passband frequency of 0.5 Hz and a stopband frequency of 0.45 Hz. For low-pass filtering, a least squares filter with a filter order of 2000 was applied with a passband frequency of 25 Hz and a stopband frequency of 27.5 Hz. The EEG data was downsampled to 128 Hz and subsequently normalized by subtracting the mean and dividing by the SD per epoch.

2.3.3 Neural tracking

For the neural tracking analysis, we used a forward modeling approach (i.e., encoding model), meaning that speech representations were used to predict the EEG signal (Mesgarani et al., 2014; Di Liberto et al., 2015; Holdgraf et al., 2017). Here, we were interested in both acoustic and linguistic speech representations. We relied on 8 representations, which were extracted from the stimulus story (fig. 1 B). We considered the envelope and envelope onsets as acoustic speech representations. Phoneme and word onsets represented segmentation of speech. Phoneme surprisal and phoneme entropy were considered as linguistic representations at the phoneme level, word surprisal and word frequency at the word level.

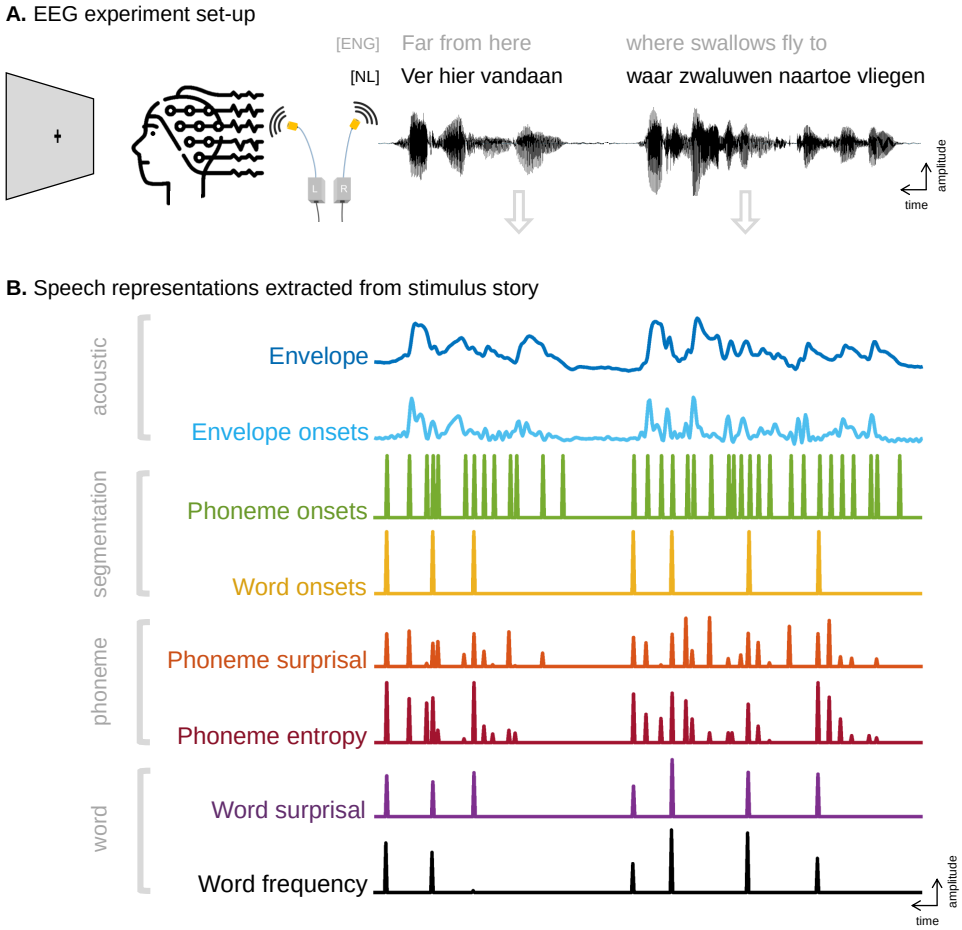

Figure 1: **EEG experiment set-up and extraction of speech representations from the stimulus story. A.** Participants listened to a story in Dutch (Flemish dialect) while EEG data was recorded. They were asked to look at a fixation cross while listening. The first 2 phrases of the story are visualized as written text (with an English translation) and audio signal. **B.** From the audio signal as depicted in panel A, 8 speech representations were extracted that reflect acoustic and linguistic properties of the story.

Envelope. The envelope was extracted by using a gammatone filter bank of 28 channels with center frequencies between 50 and 5000 Hz. We applied a power law on the absolute values and averaged across the 28 envelopes (same parameters as in Vanthornhout et al. (2018)). These steps were applied because they model the auditory system's structure (Biesmans et al., 2017).

Envelope onsets. The envelope onsets were calculated as the half-wave rectification of the first derivative of the envelope.

Phoneme and word onsets. Phoneme and word onsets were coded as dummy variables with a pulse at the beginning of each phoneme, respectively of each word. In order to get there, an aligner (Duchateau et al., 2009) was used to create alignment files containing the timing of each phoneme, respectively each word for the audio files of the stimulus story.

Phoneme surprisal. Phoneme surprisal was computed as the negative logarithm of the phoneme probability in the activated cohort. The activated cohort refers to words activated by initial phonemes, e.g., after hearing the sound /pl/, the activated cohort consists of words such as play, plus and plural. Phoneme surprisal is thus a representation of how surprising a phoneme is given the activated cohort. The first phoneme of each word included all words in the active cohort. Phoneme surprisal was calculated based on the SUBTLEX-NL database (Keuleers et al., 2010) and a custom pronunciation dictionary.

Phoneme entropy. Phoneme entropy is a measure of the degree of competition between the words congruent with the current phonemic input. For instance, after hearing the sounds /pl/, many possible words are present in the activated cohort (n=999), mirrored in a high degree of competition. Yet, after the next phonemes, the number of possible words decreases (e.g., for /plu/, n=162 and for /plur/, n=19), and thus the activated cohort decreases, reflected in a lower degree of competition. The degree of competition was computed as the Shannon entropy of the words in the activated cohort. Again, the first phoneme of each word included all words in the active cohort. Phoneme entropy was also calculated based on the SUBTLEX-NL database (Keuleers et al., 2010) and a custom pronunciation dictionary.

Word surprisal. Word surprisal was calculated as the negative logarithm of the conditional probability of a given word based on the 4 previous words. Word surprisal thus represents how surprising a word is, taking into account the 4 previous words. Word surprisal was calculated using the 5-gram model by Verwimp et al. (2019).

Word frequency. Word frequency was calculated as the negative logarithm of the unigram probability and represents how frequently words are used. Given that we used the negative logarithm, words with a higher frequency are reflected in lower scores. Word frequency was also calculated using the 5-gram model by Verwimp et al. (2019).

Isolating speech processing levels. An issue when analyzing acoustic and linguistic speech representations is their collinearity, e.g., some top-down linguistic cues at the phoneme and word level are also represented in the speech envelope, such as word boundaries and syllable stress, which contain semantic

cues. Vice versa, some bottom-up acoustic information is also present in linguistic phoneme and word level representations (Gillis et al., 2022), e.g., due to amplitude rises and falls defining the boundaries between (pre-)lexical units. Neural signals related to acoustic processing can thus also be captured by neural tracking of linguistic speech representations and vice versa.

In this study, we were interested in disentangling - as far as possible - different speech processing mechanisms. This is important should neural tracking be used for diagnosing different language profiles of aphasia in the future, e.g., disentangle individuals that have more problems with acoustic, phonological or semantic processing. Therefore, we regressed out the variance explained by the speech representations that we were not interested in. Specifically, we first applied an ordinary least squares (OLS) regression analysis without regularization, using the EEG signal as dependent variable and speech representations as predictors that share variance with the representations of interest (table 2). All the data was used for training and testing, such that all activity related to the collinear speech representations was regressed out. As a second step, we then used the residual EEG signal of that regression as input for the encoding model in order to model the relationship with the speech representations of interest. The constellation of speech representations used as predictors in the encoding models is illustrated in table 2.

Table 2: Constellation of speech representations in the 4 encoding models.

Regressing out representations not of interest	**Boosting on residuals (representations of interest)**	**Encoding model/ referred to as**
phoneme onsets word onsets phoneme surprisal phoneme entropy word surprisal word frequency	envelope envelope onsets	acoustic
envelope envelope onsets phoneme surprisal phoneme entropy word surprisal word frequency	phoneme onsets word onsets	segmentation
envelope envelope onsets phoneme onsets word onsets*	phoneme surprisal phoneme entropy	phoneme level
envelope envelope onsets phoneme onsets word onsets*	word surprisal word frequency	word level

*We decided against regressing out phoneme level linguistic representations for the word level model and vice-versa, because we expected that more data would be needed to get meaningful results from such an analysis.

Computation of temporal response function and prediction accuracy. For the encoding analysis of the speech representation of interest, we applied the boosting procedure (David et al., 2007). We made use of the Eelbrain toolbox for this step (https://doi.org/10.5281/zenodo.6992921) (Brodbeck et al., 2021). The data was split into a held-out test set of roughly 2 minutes of the data and a training set containing the rest of the data. The training set was used to perform regression analyses on the residual

EEG signal with the speech representation as predictor, for a number of time-shifted versions, resulting in the temporal response function (TRF). The number of time-shifted versions was defined by the chosen integration window length, i.e., -0.1078 to 0.6109 seconds, and the sampling frequency (*(ending time lag-starting time lag)/(1/sampling frequency)*), which resulted in 92 time shifts. The TRF thus provides information about *how* the neural response pattern operates across processing time. This information and the speech representation were then used to predict EEG signals for the test set of the data. The predicted EEG signal was correlated with the originally recorded EEG signal, providing a measure of *how well* the speech representation is encoded in the brain for each electrode, hereafter referred to as prediction accuracy. The higher the prediction accuracy is, the stronger the speech representation is encoded in the EEG signal. This procedure was repeated for different partitions of the data into training and test sets, such that each part of the data was once used as test set, resulting in 12 folds (i.e., k-fold cross-validation). For the TRF, the 12 folds were averaged across to get robust outcome measures. To arrive at the final prediction accuracy, the folds of the predicted EEG signal were concatenated and subsequently correlated with the originally recorded EEG signal.

2.3.4 Determination of the TRF peak latency ranges

To determine in which time windows to perform cluster-based permutation tests, we used the built-in MATLAB function *findpeaks* (MATLAB, 2016) to identify peaks in the TRF. Peak latencies were extracted per speech representation and per participant. An arbitrary range of 150 ms was defined around the average latency of the control group per identified peak (table 3). The average latency per peak of the aphasia group was very similar to the control group (the largest difference among all peaks was 18 ms), such that the selected ranges were valid to find differences between the aphasia and control group. For time ranges that started before 0, the lower bound was set to 0. The 150 ms ranges, as indicated in table 3 and visualized in supplementary figure S.5, were used as time windows to perform cluster-based permutation tests on the TRF (section 2.4 for details). As 26 peaks were found across speech representations, we conducted 26 cluster-based permutation tests.

2.4 Statistical analysis

Statistical analyses were performed in R (R Core Team, 2017) and in the Python (Van Rossum and Drake Jr, 1995) toolbox Eelbrain (Brodbeck, 2020).

2.4.1 Group comparison of the level of neural tracking

For the prediction accuracy analysis, we averaged across all 64 electrodes and conducted a linear model in R in order to investigate group differences and to regress out the covariates, i.e., *average prediction accuracy* $\sim$ *group + age + hearing + cognition + alertness + fatigue*. We repeated this for each of

Table 3: TRF peak ranges of the control group used for defining time windows for cluster-based permutation testing.

Speech representation	**Average peak latency (ms)**	**Range (ms)**
envelope	29	0 - 104
	163	88 - 238
envelope onsets	44	0 - 119
	102	27 - 177
	209	134 - 284
phoneme onsets	61	0 - 136
	252	177 - 327
	305	230 - 380
word onsets	114	39 - 189
	190	115 - 265
	308	233 - 383
	446	371 - 521
phoneme surprisal	221	146 - 296
	360	285 - 435
	354	279 - 429
phoneme entropy	243	168 - 318
	389	314 - 464
	416	341 - 491
word surprisal	122	47 - 197
	199	124 - 274
	320	245 - 395
	428	353 - 503
word frequency	122	47 - 197
	197	122 - 272
	330	255 - 405
	459	384 - 534

the 4 encoding models, i.e. the acoustic, segmentation, phoneme and word level model. We checked the normality assumptions using the Shapiro-Wilk test, which failed to reject H0 for each model. The homogeneity of variances assumption was not met in any of the 4 models. Nonetheless, we interpreted the linear models, given that the residuals were normally distributed. As each model was based on a different dataset, we did not control for multiple comparisons in this analysis.

As a second analysis of the prediction accuracies, we conducted a cluster-based permutation test to see if certain electrodes drive the difference between groups. To this end, we used the function *testnd.TTestIndependent* from the Eelbrain toolbox (https://doi.org/10.5281/zenodo.6992921). The cluster-based permutation test is a mass-univariate independent samples t-test that relies on bootstrapping (see Gillis et al. (2021) for more details). We defined a maximum p-value of 0.05 as threshold. We report the number of electrodes in the significant cluster, the v-value and the p-value.

2.4.2 Group comparison of the neural response pattern

To investigate the TRF pattern differences between the control group and the aphasia group, we applied cluster-based permutation tests in the arbitrary integration window ranges identified by the peak latency extraction (table 3). The same function and parameters were used as for the prediction accuracy. As there were multiple peaks identified for each of the 8 speech representations, we corrected the p-value for multiple comparisons within speech representation using the false discovery rate (FDR). Given that this

is an exploratory study, we report the uncorrected and corrected significance thresholds.

3 Results

3.1 Prediction accuracy

When averaging the prediction accuracy across all electrodes, we found a significant group difference in the acoustic model (group effect: F = 7.456, p = 0.008) and the segmentation model (group effect: F = 4.868, p = 0.031; fig. 2 A and C). The healthy control group showed higher prediction accuracies in comparison to the aphasia group. For both models, the group effect was present despite controlling for the influence of age, hearing, cognition, alertness and fatigue in the model. None of the covariates significantly explained the prediction accuracies, except for the acoustic model, where alertness significantly explained part of the variance in neural tracking (F = 4.363, p = 0.041). The phoneme and word level models did not show a significant group difference. The results of all models are reported in table 4.

Table 4: Results of the group effect and covariates on the prediction accuracy models.

Effect	**adj.R^2**	**F**	**DF**	**Estimate**	**Standard error**	**p**
			Acoustic			
Model performance	0.105	2.176	(6, 54)		0.013	0.059
Group		7.456	1	5.24E-03	4.43E-03	**0.008**
Age		0.6023	1	6.99E-05	1.88E-04	0.441
Hearing		0.168	1	4.46E-05	1.43E-04	0.682
Cognition		0.233	1	5.58E-05	1.49E-04	0.63
Alertness		4.363	1	4.25E-03	2.58E-03	**0.041**
Fatigue		0.231	1	1.42E-03	2.96E-03	0.632
			Segmentation			
Model performance	0.051	1.545	(6, 54)		5.00E-03	0.181
Group		4.868	1	2.92E-03	1.78E-03	**0.031**
Age		0.001	1	-4.59E-05	7.54E-05	0.974
Hearing		3.052	1	1.01E-04	5.73E-05	0.086
Cognition		0.156	1	3.00E-05	5.96E-05	0.694
Alertness		0.729	1	1.11E-03	1.04E-03	0.396
Fatigue		0.462	1	-8.07E-04	1.19E-03	0.499
			Phoneme			
Model performance	0.006	1.066	(6, 54)		5.00E-03	0.394
Group		2.745	1	3.28E-03	1.79E-03	0.103
Age		0	1	-5.79E-05	7.60E-05	0.999
Hearing		1.861	1	6.78E-05	5.78E-05	0.178
Cognition		0.551	1	-3.42E-05	6.01E-05	0.461
Alertness		0.357	1	9.99E-04	1.04E-03	0.552
Fatigue		0.881	1	-1.12E-03	1.20E-03	0.351
			Word			
Model performance	-0.007	0.928	(6, 54)		4.00E-03	0.482
Group		2.673	1	2.42E-03	1.54E-03	0.107
Age		0.449	1	-1.66E-06	6.52E-05	0.505
Hearing		1.412	1	5.36E-05	4.96E-05	0.239
Cognition		0.136	1	-1.17E-05	5.15E-05	0.712
Alertness		0.262	1	7.31E-04	8.95E-04	0.61
Fatigue		0.637	1	-8.19E-04	1.03E-03	0.428

DF=degrees of freedom; significant effects are marked in bold.

The cluster-based permutation tests confirmed these results and gave further information about what cluster of electrodes is driving the difference between the control group and the aphasia group. The acoustic model revealed 2 clusters that differed between groups (fig. 2 B). Specifically, a frontal left-lateralized cluster (number of sensors = 8, v = 21.798, p = 0.035) and a posterior cluster (number of sensors = 13, v = 40.251, p = 0.007) both displayed decreased prediction accuracies in IWA. The

segmentation model revealed one cluster that differed between groups (number of sensors = 9, v = 23.661, p = 0.008; fig. 2 D), namely displaying decreased prediction accuracies in IWA. The phoneme and word level models did not show any significant group differences.

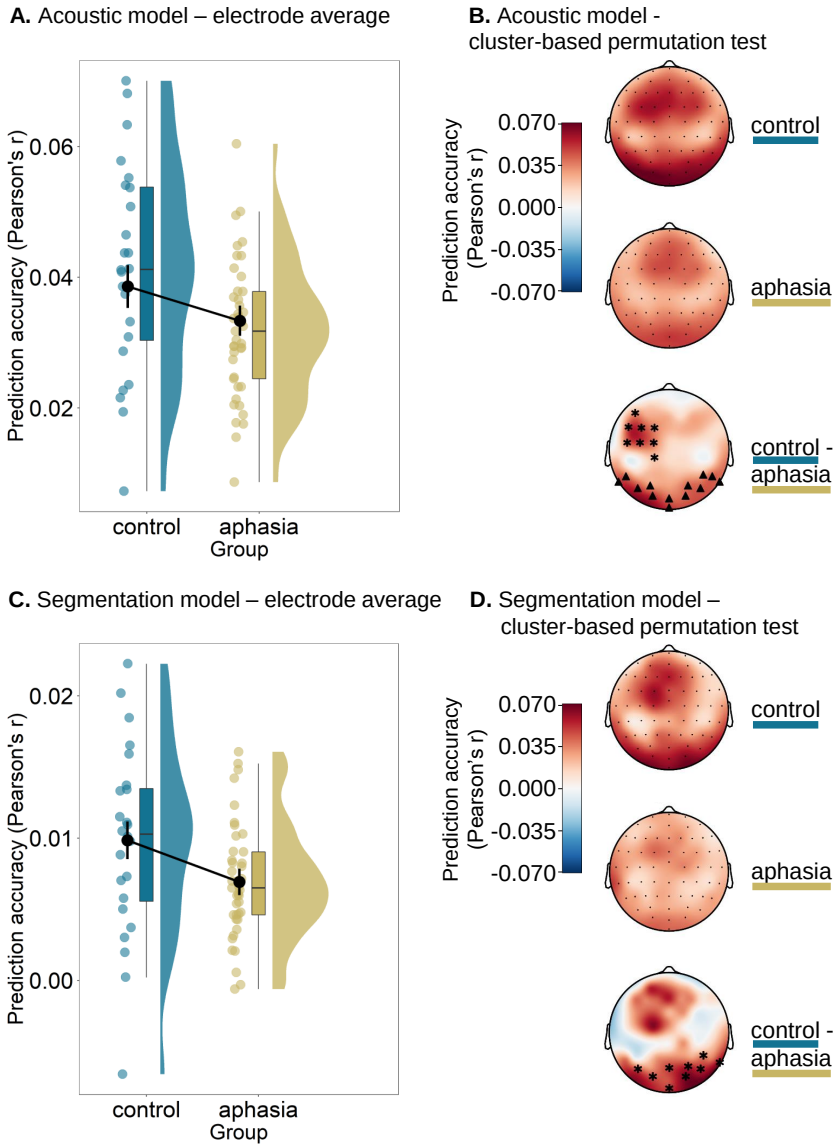

Figure 2: **Individuals with aphasia display decreased neural tracking of acoustic and segmentation-related speech representations - across all electrodes and in local clusters.** **A.** When averaging the prediction accuracies of the acoustic model across all 64 electrodes, we found a significant group difference, even when we controlled for age, hearing and cognition. The acoustic model consists of the speech envelope and its onsets as speech representations. **B.** The cluster-based permutation test revealed 2 clusters that significantly differed between groups, showing lower prediction accuracies in individuals with aphasia. The lowest topoplot consists of the difference between the control group and the aphasia group and the significant clusters are marked with stars and triangles. **C.** When averaging the prediction accuracies of the segmentation model across all 64 electrodes, we found a significant group difference, even when we controlled for age, hearing and cognition. The segmentation model consists of the onsets of phonemes and words as speech representations. **D.** The cluster-based permutation test revealed one cluster that significantly differed between groups, showing lower prediction accuracies in individuals with aphasia. The lowest topoplot consists of the difference between the control group and the aphasia group and the significant cluster is marked with stars.

3.2 Temporal response function

For the speech envelope TRF, we found 2 clusters that differed between the control and aphasia group around 180 ms (fig. 3 A; frontal left cluster: time(ms) = [95 243], number of sensors = 26, v = 550.36, p< 0.001; posterior cluster: time(ms) = [134 243], number of sensors = 16, v = -423.81, p = 0.007). The 2 clusters were located left-sided frontally and posteriorly, which is similar to the results from the prediction accuracy of the acoustic model (fig. 2 B). After correction for multiple comparisons via FDR (for n=2 comparisons due to the tested time ranges per speech representations, see table 3), these results remained significant (frontal left: p = 0.001; posterior: p = 0.015). Looking at the neural response to phoneme onsets, we found a cluster that differed between the control group and the aphasia group in frontal electrodes around 280 ms (time(ms) = [235 384], number of sensors = 11, v = 255.01, p = 0.036). This group effect in the neural response to phoneme onsets did not survive correction for multiple comparisons.

No group difference clusters were found for the speech representations envelope onsets, phoneme surprisal and phoneme entropy. However, for the speech representations at the word level, i.e. word onsets, word surprisal and word frequency, clusters that differed between groups were observed (fig. 3 B, C and D). The neural response patterns to word onsets displayed 2 clusters that differed between the control and aphasia group around 195 ms (frontal left-lateralized cluster: time(ms) = [142 243], number of sensors = 11, v = -249.5, p= 0.018; posterior cluster: time(ms) = [157 267], number of sensors = 10, v = 207.5, p = 0.037). The neural response patterns to word surprisal displayed a cluster that differed between the control and aphasia group that spread across 2 negative peaks, around 135 ms (difference in posterior left electrodes) and around 195 ms (difference in frontal left electrodes) (time(ms) = [79 204], number of sensors = 21, v = -228.65, p= 0.019). The neural response patterns to word frequency displayed a cluster that differed between the control and aphasia group around 210 ms (time(ms) = [157 275], number of sensors = 15, v = -197.26, p= 0.027). None of these effects survived the correction for multiple comparisons via FDR.

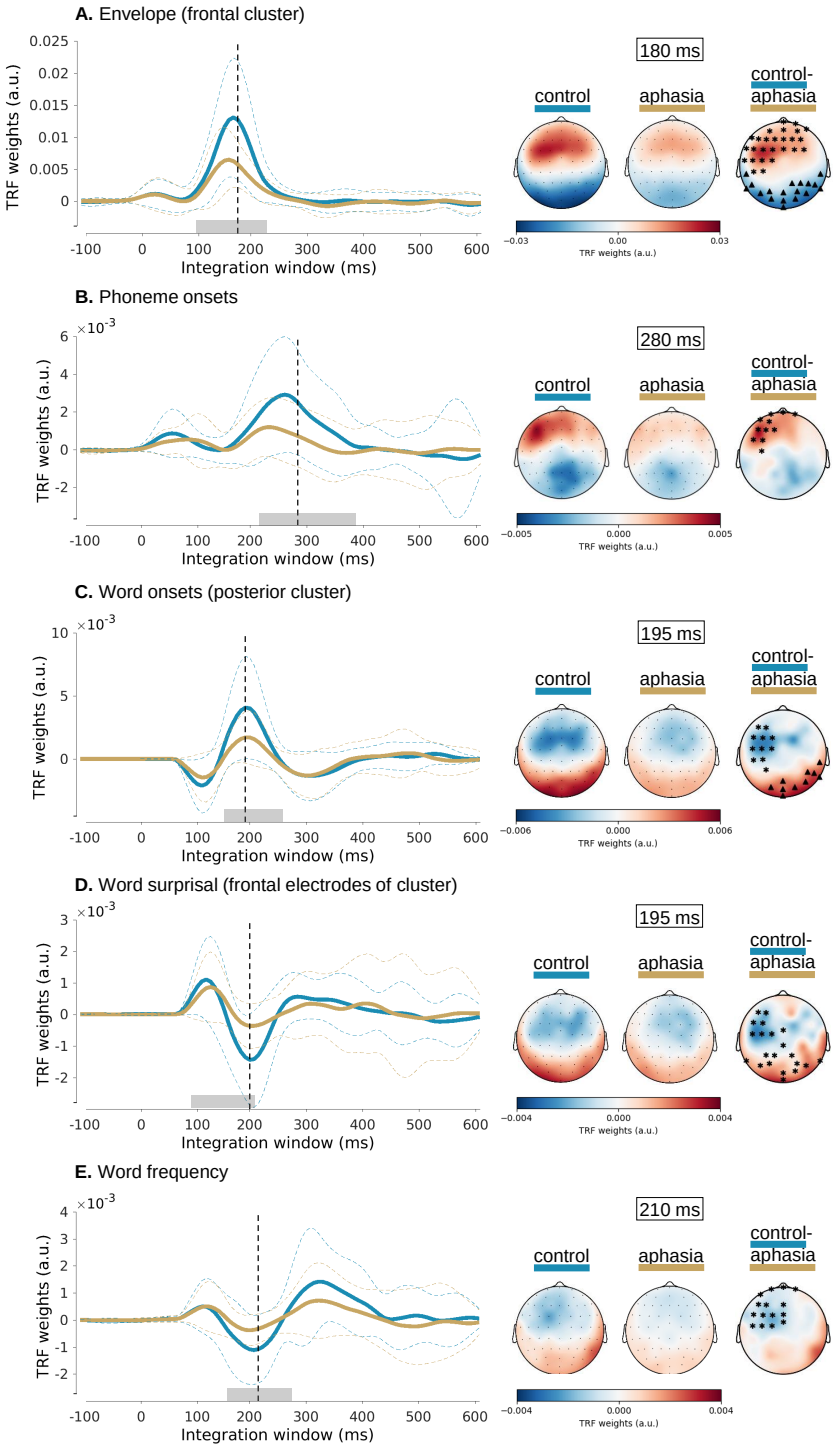

Figure 3: **Individuals with aphasia show reduced neural response amplitudes to acoustic and linguistic speech representations in local clusters.** In each of the 5 panels, the control and aphasia group average TRFs are plotted. For the left-sided figures, we averaged across the electrodes in the identified clusters. For the right-sided figures, the topoplots are shown at the time point indicated by the dashed line in the left-sided figures. The last topoplot on each panel displays the difference between the control group and the aphasia group, with the clusters marked with stars and triangles. **A.** The neural response pattern to the speech envelope revealed 2 clusters around 180 ms, a frontal one (visualized) and a posterior one (not visualized). **B.** The neural response pattern to the phoneme onsets revealed a frontal cluster around 280 ms. **C.** The neural response pattern to the word onsets revealed 2 clusters around 195 ms, a frontal one (not visualized) and a posterior one (visualized). **D.** The neural response pattern to word surprisal revealed a cluster with 2 peaks, a posterior peak around 135 ms and a frontal peak around 195 ms (electrodes of this latter peak are visualized). **E.** The neural response pattern to the word frequency revealed a frontal cluster around 210 ms.

4 Discussion

In this study, we aimed to investigate whether IWA display different neural tracking of continuous speech than age-matched healthy controls at multiple processing levels (acoustic to linguistic). To this end, we collected EEG data of 41 IWA and 24 healthy controls while they listened to a continuous narrative. Speech representations were derived from the narrative and their relation to the EEG signal studied, i.e., neural tracking. This method allows to explore *how* spatio-temporal neural response patterns operate during continuous speech at multiple processing levels (i.e., TRFs). Further, this method provides a measure of *how well* speech representations are encoded in the EEG data (i.e., prediction accuracy). Concerning prediction accuracies, group differences between IWA and healthy controls were found for processing acoustic and segmentation-related speech representations, both located in posterior clusters and to some extent (acoustic processing) also in a left frontal cluster (fig. 2). Regarding TRFs, group differences in processing acoustic, segmentation and word level speech representations were observed at different peaks between 135-280 ms, mainly located in left-lateralized frontal and posterior regions (fig. 3). However, as there were multiple TRF peaks identified per speech representation, we corrected for multiple comparisons and found that only the clusters identified in the envelope TRF were robust group differences. Nonetheless, as this is an exploratory study, we will discuss all findings here because they can help to elicit more concrete hypotheses in future investigations.

To date, neural tracking of acoustic and linguistic speech representations has not yet been investigated in post-stroke aphasia. A study in individuals with PPA, a form of dementia that surfaces as language impairment in its initial stages, has however reported increased speech envelope tracking in the theta frequency band compared to healthy controls (Dial et al., 2021). The authors hypothesized that the increased envelope tracking is related to the underlying physiological changes in PPA, i.e., a hypersynchrony between frontal and temporo-parietal cortex as well as a hyperactivity in the frontal cortex (Dial et al., 2021). Given the fundamentally different etiologies of aphasia after stroke and PPA, we did not base any hypotheses on this study. Indeed, we found a rather contrasting pattern of results in the current study, namely decreased acoustic neural tracking in IWA after stroke (fig. 2 A and B). We controlled for the variance explained by segmentation and linguistic speech representations in the acoustic model in order to yield a purer measure of acoustic processing. The observed group difference was also present despite controlling for the variance explained by age, hearing, cognition, alertness and fatigue. Of the covariates, only alertness significantly explained a part of the variance in the acoustic model. Attention has been found to modulate speech envelope tracking (Vanthornhout et al., 2019; Lesenfants and Francart, 2020). Here, the group effect also explained parts of the variance despite the effect of alertness, thus our results are not alone explained by attention effects. Nonetheless, it will be important in future studies of neural tracking in IWA to continue to implement behavioral measures of alertness and attention in the EEG

protocol.

The envelope TRF confirms the finding of the acoustic prediction accuracy model, namely decreased amplitudes in IWA over left frontal and posterior electrodes, additionally revealing that this difference occurred around 180 ms neural processing time. These results may indicate that IWA track the slow amplitude modulations of speech, which are essential for speech understanding (Shannon et al., 1995; Zeng et al., 2005; Xu and Pfingst, 2008; Oganian and Chang, 2019), to a lesser extent than age-matched healthy controls. Due to controlling the variance explained by the segmentation and linguistic speech representations, the envelope TRF mainly contains the response to acoustic properties of speech. This would mean that IWA also show impaired processing of speech acoustics. This is in line with findings from Kries et al. (2022, biorxiv), who found that 76% of IWA had a low-level acoustic or phonemic processing impairment.

At the sub-lexical and lexical segmentation level, we found decreased prediction accuracies in IWA compared to healthy controls. Our segmentation model consists of 2 speech representations containing pulses at the onset of each phoneme and word respectively. The TRF analysis revealed locally decreased amplitudes in the neural response to phoneme onsets in IWA at a peak around 280 ms as well as in the neural response to word onsets at a peak around 195 ms. These findings may indicate that IWA have a decreased performance when it comes to parsing continuous speech. Humans segment continuous speech by making use of strategies such as analysis of prosodic contours (bottom-up processes), making use of knowledge about distributional processing of phonological information and about statistical regularities in word-to-object co-occurrences (top-down processes) (Smith and Yu, 2008; Thiessen and Erickson, 2013; Suanda et al., 2014; Fló et al., 2019). Thus, sub-lexical and lexical segmentation of continuous speech is a product of the interplay between bottom-up and top-down processes (David et al., 2007; Shuai et al., 2014; Gaspers et al., 2017). Based on our findings, these processes necessary for speech segmentation may be impaired in IWA.

EEG experiments that examined ERPs have found the N400 to be related to semantic activation and integration into the sentence context (Kuperberg and Jaeger, 2016). N400 studies in IWA reported that IWA in comparison to healthy controls have increased latencies of the N400 (Chang et al., 2016; Kawohl et al., 2010; Khachatryan et al., 2017; Sheppard et al., 2017; Lice and Palmović, 2017) and attenuated amplitudes (Robson et al., 2017; Sheppard et al., 2017; Kielar et al., 2012; Räling et al., 2016; Lice and Palmović, 2017). Given the similarity between the N400 effects and the neural response pattern to word surprisal (Michaelov and Bergen, 2020; Lopopolo and Rabovsky, 2022), we hypothesized to see differences at the linguistic word level (i.e., word surprisal and word frequency) at a time window between 350 and 450 ms. However, we did not find a group difference in the time window of the N400 in the word surprisal and word frequency TRFs. This may be due to the fact that older adults generally seem to have reduced

neural tracking of linguistic speech representations (Gillis and Kries et al., 2023). All participants in the current study, healthy age-matched controls as well as IWA, were on average 70 years old. Older adults may use different strategies to process lexical meaning than those captured by word surprisal and word frequency (Federmeier et al., 2002; Wlotko et al., 2010; Spreng and Turner, 2019; Gillis and Kries et al., 2023). More research is needed to determine an ideal set of speech representations to capture semantic processing in healthy older adults, which can subsequently be translated to aphasia research.

Surprisingly, we found that IWA have decreased amplitudes in word surprisal and word frequency TRFs around 200 ms. This peak is in line results from Gillis and Kries et al. (2023), where it was present in older, but not younger adults. This peak may be related to lexical segmentation, since the word onsets TRF also showed a group difference at the same latency and over similar electrodes. While we regressed out the influence of word onsets to analyze the response to word surprisal and word frequency and vice-versa, the pulses in the word surprisal and word frequency speech representations were set at the beginning of the word and thus inherently also relate to a certain extent to lexical segmentation.

The IWA that participated in this study all had a left-hemispheric or bilateral lesion caused by stroke and the data was collected in the chronic phase after stroke (i.e., $\geq$6 months), the median time that had passed since stroke onset being 17 months. Stroke can cause changes in cerebral blood flow (Rabiller et al., 2015; Brumm et al., 2010) and can create cavities filled with cerebro-spinal fluid at the lesion site (Zbesko et al., 2018; Piastra et al., 2022). Especially the latter mechanism prevails also into the chronic phase after stroke (Piastra et al., 2022; Salinet et al., 2014; Zbesko et al., 2018). Both aspects can impact the conductivity of the neurophysiological activity that is picked up by the EEG, which can lead to asymmetries in topography or changes in specific frequency bands (Vorwerk et al., 2014; Cohen et al., 2015; Park et al., 2016; Cassidy et al., 2020). Therefore, in the following paragraph, we will discuss whether the decreased neural tracking effects that we observed in IWA may be related to these underlying anatomical changes that occur after stroke and influence the EEG signal or whether they are indeed a trace of decreased processing of speech.

Many, but not all, of the clusters that differed between healthy controls and IWA occurred over left-sided electrodes (fig. 2 and 3). This region coincides with the region that is impacted by left-hemipsheric lesions in the area supplied by the middle cerebral artery, which is the lesion location for 79% of IWA in this study (of whom we had access to lesion information; table S.1). Thus, the lesion and hence, the altered conductivity, might influence the EEG signal over these electrodes. However, some group differences were found in clusters that were not located over the main lesion areas of the current aphasia sample (fig. 2 and 3). These group difference clusters mostly occurred over posterior electrodes. Furthermore, the EEG analysis method that we used here is not a direct measure of the raw EEG signal, in contrast to ERP paradigms, for which an average of the EEG signal is calculated across time-locked trials. For the

neural tracking analysis, the relation between the EEG signal and the speech representation is modeled for time-shifted versions of both signals. The model fits of each of the time-shifted models result in the TRF. A larger stimulus-related brain response captured by the EEG signal will also result in larger TRF amplitudes, thus the neural response amplitudes might be impacted by the lesion-induced changes in conductivity of the neurophysiological activity. However, the prediction accuracies are computed as the correlation between the recorded EEG signal and the EEG signal predicted via modeling of the TRF and the speech representation, all computed within-subject. This correlation does not take into account the absolute amplitude of the signals it compares. This means that the amplitude of the EEG signal does not have an influence on the prediction accuracy results. Therefore, the generally lower prediction accuracies of the acoustic and segmentation model in IWA as compared to healthy controls likely reflect decreased tracking of acoustic and segmentation-related cues in the speech signal (fig. 2). Nonetheless, in future studies of neural tracking in post-stroke patients, it would be useful to also systematically collect magneto-resonance imaging (MRI) data and take the lesion location and volume into account.

In sum, our results show that measurements of neural tracking of acoustic and linguistic speech representations may be a promising avenue for future diagnostic and therapeutic applications. Especially the decrease in IWA in processing of acoustic cues, such as the amplitude fluctuations, and the onsets of phonemes and words seem to be rather robust effects. Future studies may confirm the potential role of neural tracking of acoustic and linguistic speech representations to provide detailed profiles of language processing difficulties in IWA (i.e., acoustic, phonological, semantic). However, confounding factors, such as effects of the stroke lesion on the EEG signal need to be better understood and taken into account in future investigations of neural tracking of speech in aphasia. An interesting approach to address this issue could be the recruitment of a control group consisting of individuals with a stroke without aphasia.

Once neural tracking in aphasia is better understood, the application potential of this method could be manifold. A study that is currently in preparation found that IWA can be distinguished from healthy controls with 83% accuracy based on neural envelope tracking with mutual information of only 5 to 7 minutes of EEG data (De Clercq et al., *in preparation*). Looking a step further into the future, an aphasia diagnosis based on processing levels of different speech representations could complement behavioral diagnosis and inform speech-language pathologists further which functions should be trained in therapy. Test-retest practice effects (i.e., improved performance on repeated tests due to remembering items or training test-specific skills) could be avoided during therapy follow-up. Moreover, the method could be useful in the acute phase after stroke, when behavioral diagnostic tests are too exhausting for patients. Additionally, articulatory speech representations (e.g., mouth aperture, tongue protrusion (Mitra et al., 2010)) could be investigated to analyze effects of production impairments in aphasia during listening. Further, neural tracking of speech production also offers a possibility to study fluency impairments

in IWA. Due to the feasibility of EEG in the clinical context, the efficiency of the paradigm and the versatility of applications, neural tracking of naturalistic, continuous speech provides a powerful tool to study aphasia.

Data availability statement

All data generated or analyzed for this study are available on Open Science Framework (OSF) under the following link: https://osf.io/6t2ja/.

Materials availability statement

The alertness and fatigue questions are new materials and can be found in the supplementary information section S.1.1.4.

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Conflict of interest statement

No conflicts of interest, financial or otherwise, are declared by the authors.

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Supplementary material

S.1.1 Recruitment, data collection and participant details

S.1.1.1 Flowchart of recruitment procedure

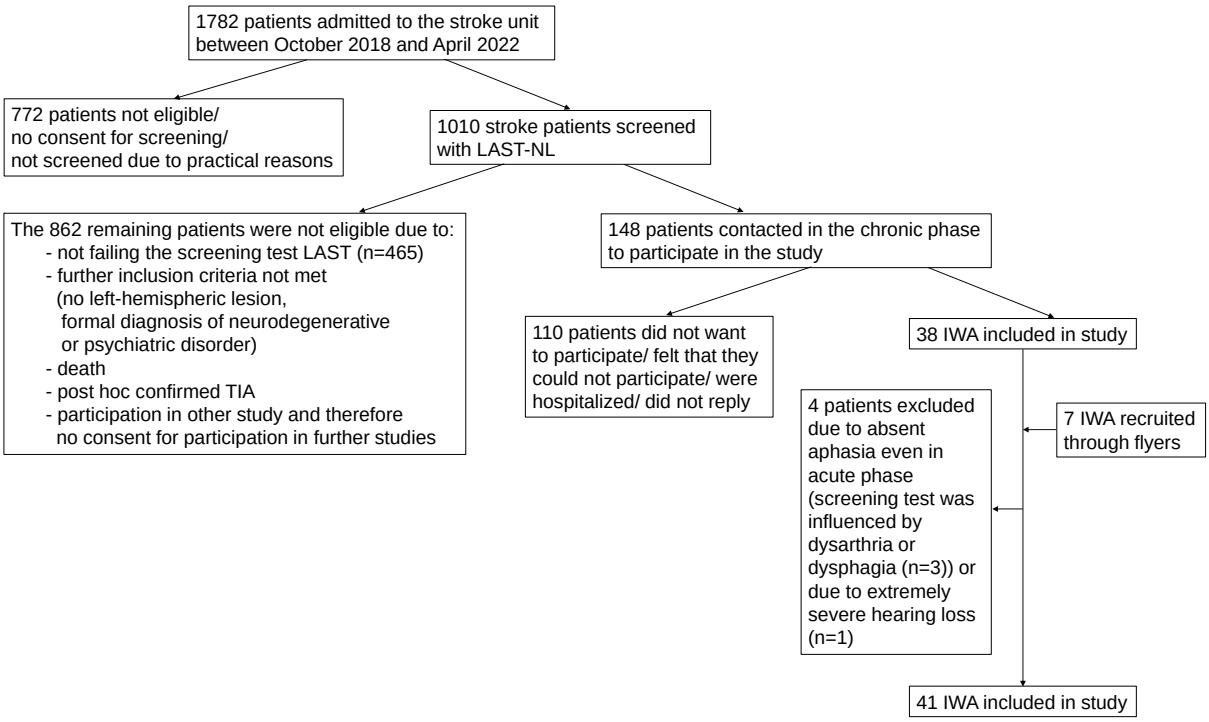

Figure S.1: **Flowchart of procedure to recruit participants with aphasia.**

S.1.1.2 Timeline of data collection

Data collection had to be stopped during winters of 2020/2021 and 2021/2022 due to the COVID-19 pandemic and thus took place mainly between the months June and October of each year. Healthy controls and participants with aphasia were recruited in alternation throughout the 3 years, which allowed us to age-match healthy controls to the IWA. Moreover this ensured that changes in EEG hardware did not influence one group more than the other. The electrode set was changed in September 2021 to prevent future problems due to extensive usage of the previous set.

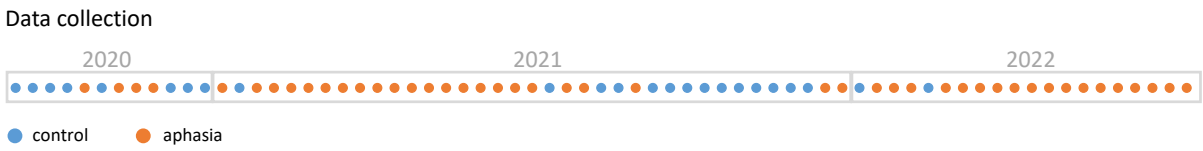

Figure S.2: **Timeline of data collection of healthy controls and participants with aphasia.**

S.1.1.3 Participant details

Table S.1: Demographic, lesion and diagnostic information of the aphasia group

ID(n=41)	age	sex	Time since stroke (months)	Stroke type	Blood vessel	Lesioned hemi-sphere	SLT	NBT score (max=276 cutoff=255)	ScreeLing score (max=72 cutoff=68)
sub-006	86	m	22.8	ischemia	VA	bilateral	yes	263	70
sub-008	71	f	21.1	ischemia	MCA	left	no	273	69
sub-009	67	m	22.6	ischemia	MCA	left	no	262	65.5
sub-010	74	m	20.6	ischemia	PCA	left	no	◇	69
sub-014	75	m	18.2	ischemia	MCA	left	yes	185	58
sub-016	68	m	18.0	ischemia	MCA	bilateral	yes	265	69
sub-017	88	m	8.2	ischemia	MCA/ PCA	bilateral	no	245	56
sub-018	61	f	29.4	ischemia	MCA	left	yes	263	72
sub-019	72	m	8.6	ischemia	PCA	left	◇	211	51
sub-020	42	m	18.7	ischemia	MCA	left	yes	273	71
sub-021	81	m	8.6	hemorrhage	◇	left	no	252	70
sub-022	78	f	8.2	hemorrhage	◇	left	yes	207	56
sub-023	90	m	22.8	ischemia	LLA	bilateral	no	265	61
sub-024	69	m	6	ischemia	MCA	left	yes	260	68.5
sub-025	69	m	11.5	ischemia	MCA	left	yes	197	58.5
sub-026	71	m	31	ischemia	MCA	left	yes	250	69
sub-027	76	m	126.2	ischemia	MCA	left	yes	254	63
sub-028	80	m	25.2	ischemia	◇	left	no	195	54
sub-029	75	m	22.6	ischemia	MCA	left	yes	193	55
sub-030	49	m	13.1	hemorrhage	◇	left	yes	217	57
sub-031	79	m	12.9	ischemia	MCA	left	yes	263	63
sub-032	76	m	94.8	ischemia	MCA	left	yes	3	28
sub-034	79	m	13.4	◇	◇	◇	yes	244	69
sub-035	64	f	31.5	ischemia	MCA/ ACA	left	yes	276	71
sub-038	60	f	368.6	◇	◇	◇	no	251	65
sub-049	85	f	8.3	ischemia	PICA	left	yes	242	65.5
sub-050	81	f	8.7	ischemia	MCA	left	yes	134	53
sub-052	72	m	120.7	◇	◇	◇	yes	175	48
sub-053	41	f	6.1	ischemia	MCA	left	yes	271	70
sub-054	69	m	17.2	ischemia	MCA	left	yes	268	69
sub-056	76	m	14.9	ischemia	MCA	left	yes	218	58
sub-059	86	m	15.2	ischemia	ICA	left	no	196	51
sub-060	70	m	15.4	ischemia	MCA	left	yes	150	◇
sub-061	54	f	12.7	ischemia	MCA	left	yes	276	72
sub-063	63	f	13.9	ischemia	MCA	left	yes	272	69.5
sub-064	81	f	12.2	ischemia	crypto.	bilateral	yes	251	62.5
sub-065	50	f	23.8	ischemia	MCA	left	yes	93	44
sub-067	40	f	38.5	ischemia	MCA	left	yes	164	56
sub-068	59	m	12.2	ischemia	MCA	left	no	247	63.5
sub-069	65	m	17.1	ischemia	MCA	left	no	258	65
sub-070	71	f	16.1	ischemia	MCA	bilateral	no	273	59.5
Total	-	27 m 14 f	-	35 ischemia 3 hemorrhage	27 MCA 3 PCA 1 ACA 1 VA 1 LLA 1 PICA 1 ICA	32 left 6 bilateral	28 yes 12 no		

SLT=speech-language therapy; VA=vertebral artery; MCA=middle cerebral artery; PCA=posterior cerebral artery; ACA=anterior cerebral artery; LLA=lateral lenticulostriate arteries; PICA=posterior inferior cerebellar artery; ICA=internal carotid artery; crypto=cryptogenic; ◇=data not available

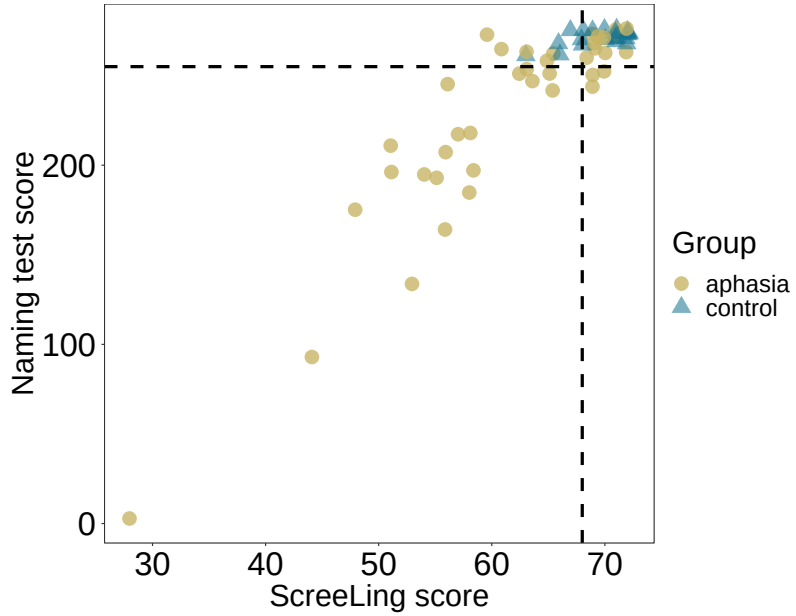

Figure S.3: **Visualization of scores on language tests. The cut-off scores are marked by the dashed lines.**

S.1.1.4 Monitoring alertness and fatigue throughout the experimental session

The subjective ratings of alertness and fatigue were administered in order to use them as covariates in statistical models. The EEG measurement took place between t1 and t2, therefore we averaged across t1 and t2 of the alertness and fatigue rating respectively, which were then used as covariate factors for the analysis of prediction accuracy models (fig. 2). We also analyzed the course of alertness and fatigue ratings between groups. Linear mixed effects models were employed for this purpose. The analysis of the alertness question revealed a main effect of group ($p<0.001$) and of time point ($p=0.049$), but no interaction effect ($p=0.226$; fig. S.4 C). Thus, across time points, individuals with aphasia were less alert than healthy controls. Post hoc testing revealed that, across all participants, people were generally less alert at the end of the protocol than at the beginning (t1 vs t3: $p=0.043$). The analysis of the fatigue question showed significant main effects (group: $p<0.001$; time point: $p=0.012$) and a significant interaction effect between group and time point ($p=0.014$; fig. S.4 D). Post hoc testing revealed that while the initial level of fatigue was at a similar level for both groups at the beginning of the test session (t1; $p=0.678$), individuals with aphasia were more tired than healthy controls after the first part of the experimental session (t2; $p<0.001$) and at the end of the protocol (t3; $p=0.001$).

We offered IWA to continue the administration of the second part of the experimental protocol on another day in case they felt too exhausted after the EEG measurement (fig. S.4 E). Indeed, 5 out of 41 IWA felt too exhausted at t2 and chose to do the rest of the tests on another day. This second session took place at the patients' homes, so that they did not have to arrange transportation to the lab again.

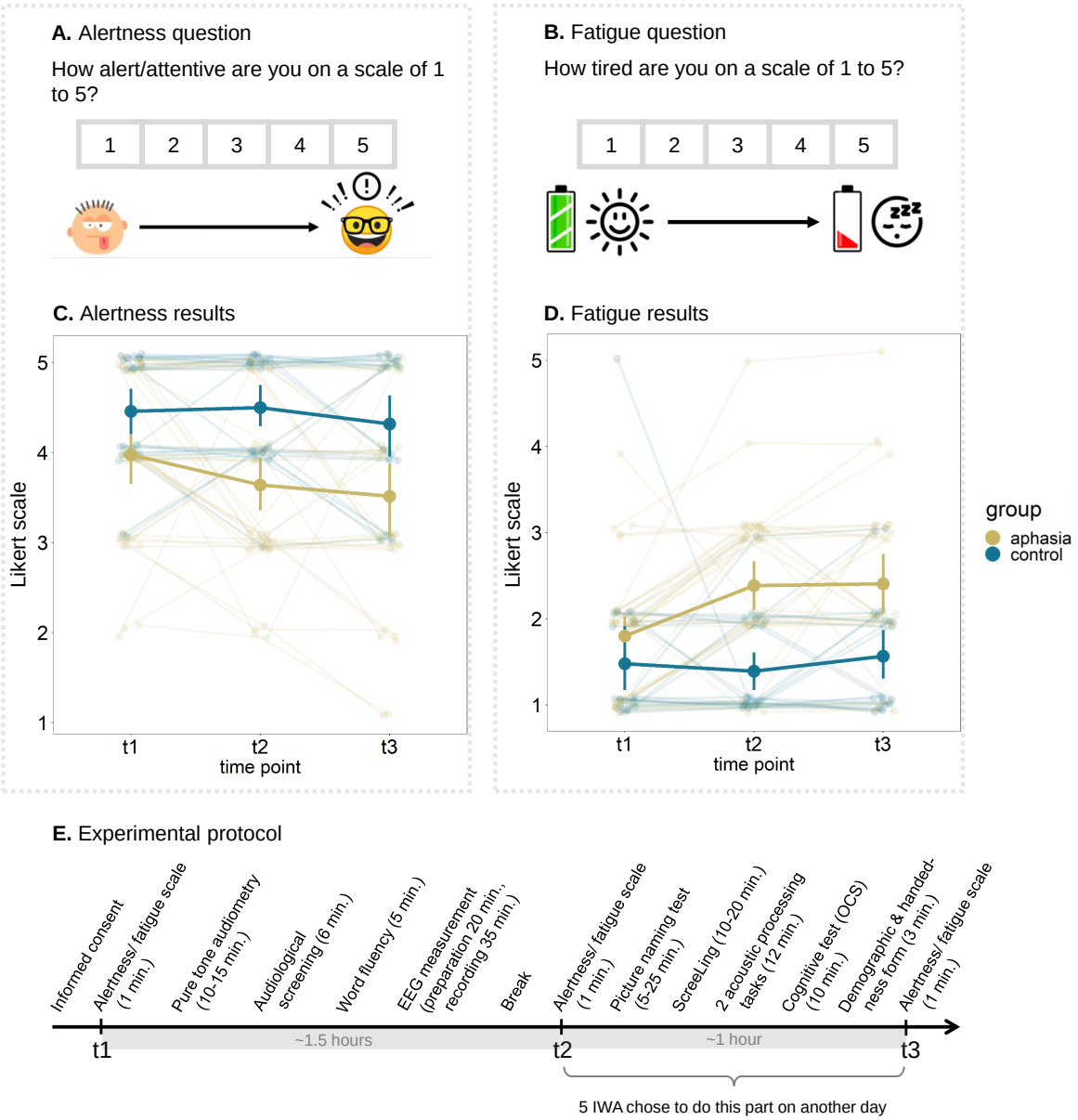

Figure S.4: **Subjective ratings of alertness and fatigue throughout the experimental session. A. and B.** The alertness and fatigue questions as presented on a tablet to the participants, with visual icons to aid comprehension of the task. The questions were simultaneously presented auditorily. **C.** A linear mixed effects model showed a main effect of group and of time point, but no interaction effect for the alertness scale. **D.** A linear mixed effects model showed a significant interaction effect between group and time point for the fatigue scale. **E.** Visualization of the experimental protocol with regard to the time points at which the alertness and fatigue scales were administered.

S.1.2 Determined TRF peak latency ranges

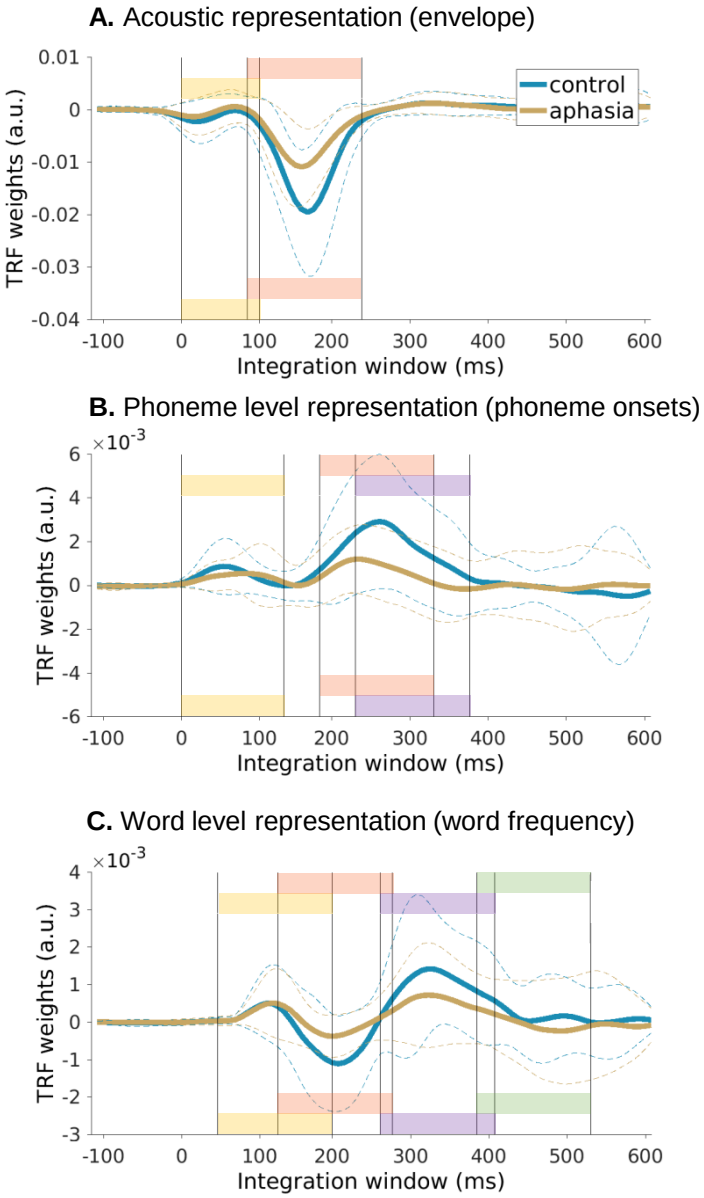

Figure S.5: **Time ranges of 150 ms visualized in 3 speech representations.**