Prior context and individual alpha frequency (IAF) influence predictive processing during language comprehension

Sophie Jano*[1], Zachariah Cross[2], Alex Chatburn[1], Matthias Schlesewsky[1], Ina Bornkessel-Schlesewsky[1]

[1]Cognitive Neuroscience Laboratory, University of South Australia
[2]Feinberg School of Medicine, Northwestern University

*Corresponding author

Abstract

The extent to which the brain predicts upcoming information during language processing remains controversial. To shed light on this debate, the present study reanalysed Nieuwland and colleagues' (2018) replication of DeLong et al. (2005). Participants (N = 356) viewed sentences containing articles and nouns of varying predictability, while their electroencephalogram was recorded. We measured event-related potentials (ERPs) preceding the critical words (namely the semantic prediction potential; SPP), in conjunction with post-word N400 patterns and individual neural metrics. ERP activity was compared with two measures of word predictability: cloze probability and lexical surprisal. In contrast to prior literature, SPP amplitudes did not increase as cloze probability increased, suggesting that the component may not reflect prediction during natural language processing. Initial N400 results at the article provided evidence against phonological prediction in language, in line with Nieuwland and colleagues' findings. Strikingly however, when the surprisal of the prior words in the sentence was included in the analysis, increases in article surprisal were associated with increased N400 amplitudes, consistent with prediction accounts. This relationship between surprisal and N400 amplitude was not observed when the surprisal of the two prior words was low, suggesting that expectation violations at the article may be overlooked under highly predictable conditions. Individual alpha frequency (IAF) also modulated the relationship between article surprisal and the N400, emphasising the importance of individual neural factors for prediction. The present study extends upon existing neurocognitive models of language and prediction more generally, by illuminating the flexible and subject-specific nature of predictive processing.

Introduction

The question of how the brain converts sensory information into abstract meaning has led to the proposal of prediction as a core mechanism underlying perception (Bar, 2011; Friston, 2005, 2010; Friston & Kiebel, 2009; Press et al., 2020). This is the major assumption of the predictive coding theory, which suggests that prior experiences are used to form generative models (Friston, 2005; Friston & Kiebel, 2009). These models are applied to predict incoming sensory inputs, thus reducing processing effort and facilitating environmental adaptation (Clark, 2013; Friston, 2010; Hohwy, 2013). Although prediction is largely accepted as an explanatory mechanism within numerous cognitive domains (Apps & Tsakiris, 2014; Horga et al., 2014; Koster-Hale & Saxe, 2013), a longstanding debate remains within the cognitive neuroscience of language between prediction-based and integrationist theories of language processing (cf., for example, Ferreira & Chantavarin, 2018). Prediction theories propose that the brain anticipates upcoming linguistic content in a top-down manner, whilst integrationist theories argue that language comprehension proceeds via the bottom-up integration of linguistic units with the prior context (Kuperberg & Jaeger, 2016; Mantegna et al., 2019; Van Petten & Luka, 2012). Although seemingly specific to language, this debate could have important implications for existing understandings of prediction as a ubiquitous cognitive mechanism (Friston, 2010; Kveraga et al., 2007), particularly if linguistic prediction does not occur. As such, clarifying the role of prediction in language processing could provide insight into whether predictive processing is indeed fundamental to general cognition as has been argued (Friston, 2010; Kveraga et al., 2007).

Prediction in language as revealed by the N400 component

As prediction and integration in language are notoriously difficult to disentangle empirically, the debate surrounding their role in linguistic processing has hinged prominently on an influential study by DeLong et al. (2005). DeLong and colleagues investigated the N400 event-related potential (ERP), which has been linked to prediction errors in language (e.g., Bornkessel-Schlesewsky & Schlesewsky, 2019; Hodapp & Rabovsky, 2021; Rabovsky et al., 2018). By the nature of its design, their experiment sought to exclude an integration-based explanation of purported prediction effects, by capitalising on the English regularity whereby the indefinite articles 'a' and 'an' precede words beginning with a consonant, and beginning with a vowel, respectively (e.g., "a kite" or "an airplane"). DeLong et al. (2005) observed larger N400 amplitudes time-locked to the article preceding unpredictable (versus predictable) nouns (e.g., "The day was breezy, so the boy went outside to fly *an* …"; the article "an" rules out the predictable continuation "kite"). As the indefinite articles 'a/an' have the same meaning, this observation is difficult to reconcile with integrationist views of the N400, which postulate that N400 differences reflect the ease with which a word's meaning can be integrated with its preceding context (Van Berkum et al., 1999; Brown & Hagoort, 1993; Chwilla & Kolk, 2000). Moreover, the N400 effect was graded in accordance with how predictable the article word was, suggesting that language comprehension involves the prediction and pre-activation of words down to the highly detailed level of speech sounds. This assumption is highly compatible with predictive coding approaches, where predictions are proposed to activate a representation of the anticipated stimulus at multiple levels of the cortical hierarchy (Rao & Ballard, 1999; Rauss & Born, 2017). Therefore, whilst there are various definitions for prediction (for discussion see Kuperberg & Jaeger, 2016), such N400-article analyses have the potential to provide evidence for the prediction of form-based linguistic attributes.

The investigation by DeLong and colleagues (2005) suggests that prediction serves as a likely mechanism for linguistic processing. This is supported by research which has observed similar

ERP effects time-locked to adjectives (Van Berkum et al., 2005) and gender-marked determiners (Wicha et al., 2004) preceding a noun, as well as prior to sign onset in sign language (Hosemann et al., 2013; Krebs et al., 2019). However, other studies have observed differential patterns (for discussion see Ito et al., 2017; Schoknecht et al., 2022), including a large-scale direct replication study by Nieuwland et al. (2018), who analysed data from 356 participants using the same stimuli as in DeLong et al. (2005). In contrast to DeLong and colleagues, Nieuwland and colleagues did not observe a more pronounced N400 following unpredictable articles. Accordingly, they suggested that, although the brain may predict upcoming contextual or semantic information, this may not extend to form-based linguistic characteristics such as speech sounds (Nieuwland et al., 2018). Therefore, the extent of prediction in language is currently unclear and may be subject to significant variability. Consequently, the mixed nature of the literature renders it important to examine other sources of variability that may influence predictive processing.

The influence of individual neural factors on prediction

An investigation of variability at the individual level may provide insight into linguistic prediction, with such variability capturing effects over and above group-level contrasts in previous studies (e.g., Roehm et al., 2013). Although individual neural differences were not considered by DeLong et al. (2005), nor by Nieuwland et al. (2018), such activity could contribute to understandings of prediction in language, particularly if prediction tendencies differ between individuals. A potential neurobiological marker that may relate to individual differences in prediction is the individual alpha frequency (IAF), the individual peak frequency within the alpha rhythm (Corcoran et al., 2018; Grandy et al., 2013; Klimesch, 1999; Surwillo, 1961). The link between IAF and prediction primarily stems from IAF's role as a trait-like marker of information processing, where those with a high IAF were shown to have faster reaction times (Klimesch et al., 1996; Surwillo, 1961, 1963) and improved discrimination of rapidly presented stimuli (Samaha & Postle, 2015). Enhanced information processing in high versus low IAF individuals may therefore translate to a stronger reliance on bottom-up perceptual information as opposed to a top-down model, resulting in more frequent model updating (Kurthen et al., 2020; however, see Bornkessel-Schlesewsky et al., 2022 for a stronger tendency to adjust predictions in low IAF individuals). As such, IAF may influence predictive processing and the extent to which sensory information is used to adjust predictions.

Despite periodic oscillatory components such as IAF traditionally being linked to cognitive processing, the importance of considering the aperiodic noise-like activity (particularly the 1/f slope of the distribution) that underlies the EEG spectra has been recently emphasised in the literature (Cross et al., 2022; Demuru & Fraschini, 2020; Dziego et al., 2023; Immink et al., 2021; Merkin et al., 2023; Ouyang et al., 2020; Voytek et al., 2015; Voytek & Knight, 2015). Although prior literature recommends controlling for this activity to directly probe periodic (i.e., oscillatory) patterns (Donoghue et al., 2020), the 1/f component has been shown to predict information processing speeds (Ouyang et al., 2020), and to mediate the relationship between age and cognitive functioning (Pathania et al., 2022; Voytek et al., 2015), suggesting that it may be relevant for cognition. Regarding prediction in language, steeper 1/f slopes have been related to prediction error processing (Cross et al., 2022), stronger N400 effects (Dave et al., 2018), and to a greater tendency to update a predictive model (Bornkessel-Schlesewsky et al., 2022). Therefore, by analysing the role of the 1/f slope in the Nieuwland et al. (2018) dataset, it may be possible to capture the individual variability relating to prediction, contributing insight to the extent of prediction in language and the role of inter-subject variability in predictive processing.

Pre-stimulus event-related potentials (ERPs) may provide insight into linguistic prediction

Whilst an analysis of individual factors may shed light on prediction, pre-stimulus ERP activity may also probe anticipatory processing more directly than post-word N400 patterns. Pre-stimulus ERPs have been proposed to reflect the transient, time-locked activity associated with prediction (Grisoni et al., 2016, 2017, 2019, 2021). Such components are generally negative-going deflections with frontal topographies and larger amplitudes preceding predictable information (Grisoni et al., 2021; León-Cabrera et al., 2019). Of note is the semantic prediction potential (SPP), which exhibits greater amplitudes in the interval preceding predictable versus unpredictable critical words, whilst demonstrating topographical variance in accordance with the meaning of each word (Grisoni et al., 2017, 2021). This provides evidence not only for prediction but for the pre-activation of the semantic characteristics of a word before it arises (Grisoni et al., 2017, 2021). Such correlates also strongly resemble the stimulus preceding negativity (SPN) ERP (León-Cabrera et al., 2019), a component associated with the subjective appraisal of prediction accuracy (Ono et al., 2021), and with feedback anticipation during reinforcement learning (Brunia et al., 2011; Morís et al., 2013). As such, whilst the absence of an N400 effect at the article (as observed in Nieuwland and colleagues' original analysis) was considered as evidence against the prediction of detailed linguistic features, a relationship between SPP amplitude and word predictability in the pre-stimulus window may provide alternative support for prediction in language, at least at the semantic level. Further, the SPP has been investigated in contexts alongside the N400 component, with high (versus low) constraint sentences eliciting larger pre-word SPP amplitudes and smaller N400 amplitudes (Grisoni et al., 2021). This inverse relationship between the N400 and the SPP may be due to the predictable nature of the words in the high-constraint sentences, which likely facilitates strong predictions (as evidenced by larger SPPs) whilst eliciting fewer prediction violations (potentially reflected in decreased N400 amplitudes; Grisoni et al., 2021). Consequently, this relationship between the SPP and the N400, and the correlations between the SPP and word predictability, highlight the potential utility of the component for understandings of prediction in language.

The present study

The current study aimed to investigate the extent of prediction in language and the role of individual neural differences in predictive processing. To do so, we analysed the event-related activity preceding the critical words in the Nieuwland et al. (2018) data (i.e., the SPP), in conjunction with the 1/f aperiodic slope and IAF. Such an analysis has the potential to shed light on the discrepancies in findings between Delong et al. (2005) and Nieuwland et al. (2018), while concomitantly deepening existing understandings of prediction as a general cognitive mechanism (Friston, 2010). It was hypothesised that increases in article and noun predictability would be associated with greater pre-stimulus SPP amplitudes, and that this would be modulated by IAF and the 1/f slope. Additionally, although not the original focus of the study, we report analyses of the N400 component to maintain consistency with Nieuwland and colleagues' investigation. After initial plots revealed differences in ERP activity at earlier stages of the sentence, we also conducted exploratory analyses including prior word surprisal, shedding light on the role of prior context in prediction.

Methods

Original study

The present study involved a reanalysis of Nieuwland et al. (2018), which included 356 participants (females = 222, mean age = 19.8 years) who were all right-handed native English speakers. Participants were recruited across nine different laboratories and the sample size was chosen to ensure that each laboratory's sample equated approximately to that of DeLong et al. (2005), who included 32 participants in total (Nieuwland et al., 2018). Participants provided informed consent for the use of their data, and ethical approval for each laboratory was sought in accordance with the requirements of the specific institution (Nieuwland et al., 2018). Cloze probability (the probability that a word will be chosen as the likely continuation based on the prior sentence context; Taylor, 1953) was used as an index of stimulus predictability. Participants viewed 80 sentences with two cloze probability continuations: a more-expected article/noun combination (e.g., "…the boy went outside to fly *a kite*") and a less-expected article/noun combination (e.g., "…the boy went outside to fly *an airplane*"). Words within each sentence were presented for 200ms sequentially on a computer screen and separated by a 300ms interstimulus interval during which participants viewed a blank screen. Following 25% of sentences, participants answered a yes/no comprehension question. EEG was recorded throughout the study to enable an analysis of the event-related activity in response to articles and nouns. For a detailed description of the study protocol and materials, the reader is directed to Nieuwland et al. (2018).

Participants

Data for 356 participants were originally obtained from the Open Science Framework (OSF) repository (see https://osf.io/eyzaq/). Five participants were removed prior to the BIDS conversion (see *Data processing* section) due to incomplete files, answering questions randomly or due to being a non-native English speaker. As such, the BIDS conversion was completed for 351 participants. Subsequent pre-processing and epoching led to the removal of 18 more participants (ten due to trigger issues that could not be resolved, and eight participants due to excessive signal noise). As such, data for 333 participants were epoched, with four participants being excluded due to a lack of trials.

Seventeen participants were also identified as having an insufficient number of epochs for the calculation of the aperiodic (1/f) slope and IAF (less than 16 trials). As all analyses included individual factors, these participants were excluded from the final sample, taking the final sample size to 312 (females = 194, mean age = 22.4 years). See *Figure 1* for a schematic of participants at each stage of the data analysis pipeline.

Data Processing

Data were first converted to the Brain Imaging Data Structure (BIDS) using the MNE-BIDS package (Appelhoff et al., 2019) in *MNE-python* version 3.8.8 (Gramfort et al., 2013), to account for file structure variations as a result of the differing EEG systems used across the laboratories. As files with the .cnt extension were unsupported by the BIDS package in python (*MNE-BIDS 0.10 Documentation*, 2022), such files were converted to the Brainvision Core Data format (Brain Products Gmbh) prior to the BIDS conversion using MATLAB (MathWorks, Natick, Massachusetts, USA). As most raw files encompassed both the experimental session and the control session, each file was then cropped to exclude the control session, as this was not of interest to the present analysis.

Data were then re-sampled to either 250Hz or 256Hz, depending on the original sampling rate, which ranged from 250Hz to 2048Hz between laboratories. Resampling occurred at an equal interval to avoid data loss when epoching (Gramfort et al., 2013), hence the two sampling frequencies. Therefore, the final sample consisted of 184 participants with data sampled at 250Hz, and 145 participants with sampling rates of 256Hz. This is not expected to have affected the single-trial ERP analyses, as samples were averaged across time intervals of interest and slight discrepancies in the number of samples per window should not introduce significant variability. Following resampling, the EEG data were re-referenced to linked mastoids, while EOGs were set as Fp1 and Fp2 across laboratories. For laboratories that used the alphabetized Biosemi system (BioSemi, 2019), EOG channels were those closest to Fp1 and Fp2 (i.e., C29 and C16, respectively). The data were filtered using a bandpass filter that ranged from 0.1 to 30Hz.

To conduct an independent component analysis (ICA), temporary epochs around events of interest were first generated. Rejection thresholds were then computed from the epochs using the *Autoreject* package in MNE-python (Jas et al, 2016), to be included in the ICA for the detection and removal of ocular artefacts. This procedure is argued to lead to more precision in the ICA, as thresholds are tailored specifically depending on the activity in segments of interest (Jas et al., 2016). The ICA was then fit to a 1Hz high pass filtered copy of the temporary epochs, to minimise the influence of noise from the inter-trial intervals. Subsequently, the ICA was applied to the raw data (See *Table 1* for average number of trials per condition). Following this, channels marked as bad were interpolated using spherical splines and the raw data were epoched around events of interest into segments ranging from -800ms to 1000ms (1.8 seconds total). The *Autoreject* function (Jas et al, 2016) was then applied to repair or remove bad epochs (average percentage of epochs rejected = 9.62%).

ERP analysis

Event-related activity was extracted within the SPP and N400 time windows on a trial-by-trial basis. The SPP window ranged from -300 to 0ms prior to the article and noun words, to encompass the length of the interstimulus intervals. The N400 time window ranged from 200ms to 500ms post-stimulus onset, in line with Nieuwland et al. (2018). To control for differences in neural activity unrelated to the experimental manipulation, epochs were also generated around the word preceding the article. The inter-stimulus interval (-300 to 0ms) preceding the word before the article (the article-1 word) was chosen as a baseline period due to its temporal proximity to the trials of interest, and because the SPP activity preceding the articles and nouns could not be used since it was the focus of the present investigation. This pre-article-1 word baseline window was not used for traditional baseline correction, but rather the mean amplitude across this window was entered as a covariate into the statistical models of SPP effects involving both the article and the noun that followed (in line with Alday, 2019). For N400 analyses at the article, activity in the pre-article window itself (-300 to 0ms preceding the article) was used as the "baseline" period, whilst for noun N400 analyses, activity in the pre-noun window (-300 to 0ms preceding the noun) was used. This activity was similarly included as a covariate for statistical modelling, and according to Alday (2019), does not need to be further interpreted once controlled for (i.e., it serves as a covariate of no interest).

To generate ERPs, *MNE-Python* (Gramfort et al., 2013) was used to calculate the mean ERP amplitude across time windows of interest. Due to differing EEG systems, one laboratory lacked channels that directly corresponded to a common 10-20 channel shared by the other laboratories. As such, a region-based approach was taken whereby SPP event-related activity was analysed over frontal regions, in line with previous research (León-Cabrera et al., 2017,

2019; Morís et al., 2013). For N400 analyses, we included the channels that were used in the original study (Cz, C3, C4, Pz, P3, and P4). However, the laboratory that used the alphabetized system did not have channels that directly corresponded to P3 and P4, and thus the closest channels were used (A7 and B4, respectively). ERP grand average plots were created using *ggplot2* in *R version 4.1.1* (Wickham, 2016). Due to the differing sampling intervals, the timing of the samples for four laboratories was adjusted by a maximum of four milliseconds to match the timing of the other laboratories. This was done for visualisation purposes only. Additionally, for ease of visualisation, channel-specific ERP plots include data from the alphabetized Biosemi channel that was closest to the shared 10-20 channel nomenclature.

Individual alpha frequency and aperiodic 1/f slope estimation

Individual alpha frequency (IAF) and the aperiodic 1/f slope were calculated at the individual level using the *Fitting Oscillations & one-over f (FOOOF)* package (version 1.0.0) in *MNE-python* (Gramfort et al., 2013). Epochs were first generated around the between sentence intervals as during this time, participants should not have been actively engaged in the task (in exception is the 25% of trials that included a comprehension question, which were removed), and thus task-related effects were likely reduced. Epochs ranged from 200ms after the final word (when the presentation of the final word had ended), to 2.2 seconds, to ensure a sufficient number of samples to obtain reliable estimates. As the between-sentence intervals were self-paced, trials in which the intervals were shorter than 2.2 seconds were removed from the analysis. Similarly to the treatment of task-related epochs, the *Autoreject* function (Jas et al., 2017) was then applied to the between-sentence epochs to repair or remove bad trials.

Following epoching, the power spectral density was computed for each epoch across all EEG channels (Donoghue et al., 2020). Channels Oz, O1, and O2 were selected, as alpha activity is prominent over occipital regions (Kirschfeld, 2005), and as prior research suggests that the relationship between 1/f and cognitive processing may be similar across the scalp (Ouyang et al., 2020). The *FOOOF* algorithm was fit to PSD estimates derived from each channel, per epoch. For the laboratory with the alphabetized system, the channels closest to Oz, O1 and O2 were used (A23, A15 and A28, respectively). Parameterization of the power spectra occurred across a frequency range of 1-30Hz. Settings for the *FOOOF* algorithm included a peak width limit of 2 to 8, a maximum peak number of four, the minimum peak height as 0.0, a peak threshold of 2.0, and a fixed aperiodic mode. To obtain individual metrics, activity across the three channels was averaged across all epochs, resulting in single-subject slope and offset values. IAF estimates were calculated by selecting peaks within the 7-13Hz range and averaging over the activity across each channel and epoch to obtain a single IAF value per participant.

Statistical analysis

Statistical model structures for the primary analyses are presented in *Table 3.* To examine effects of interest whilst accounting for random effects, linear mixed-effects models (LMMs) were computed using the *Lme4* package in *R version 4.2.2* (Bates et al., 2015). P-values were calculated using the *summary* function from the *lmerTest* package, which is based on Satterthwaite's degrees of freedom (Kuznetsova et al., 2017). The alpha level was set at 0.05 and all predictor variables were scaled and centred. Note that for the main analyses, IAF and the 1/f slope were included in the same models, specifying different interaction terms, as the relationship between the two factors was not a primary interest of the study. The model fits of these combined models also were either better or did not significantly differ from separate models for IAF and 1/f, as measured by the Akaike criterion (See *Appendix 1 – Table 1* for Akaike criterion values).

Primary and exploratory surprisal models (described in the *Exploratory surprisal analyses* section) initially failed to converge with complex random effects structures (i.e., random intercepts of item, subject and channel, and by-item and by-subject random slopes). To simplify the model structures, ERP activity was averaged over channels of interest, allowing for the removal of random intercepts of channel. However, the models either failed to converge, or exhibited singular fits, when random slopes according to all predictors were included. To avoid overfitting, by-subject and by-item random slopes according to the primary predictor of interest (critical word cloze or critical word surprisal) were instead included (for a discussion of model overspecification resulting from maximal LMM structures, see Bates et al., 2018). However, one model (model 1) failed to converge with random slopes, which were omitted. To determine whether the inclusion of random slopes improved goodness of fit, models that converged with random slopes were compared with and without the random slopes using Likelihood ratio tests (LRTs). The LRTs revealed that for all models (excluding Model 3), the inclusion of random slopes significantly improved the model fit (See *Appendix 1 – Table 2* for LRT results). Model 3 also initially only exhibited a non-singular fit with by-item, not by-subject random slopes. However, because the by-item random slopes did not improve the model fit, they were removed.

When investigating the effect of word predictability (operationalized as cloze probability) on the SPP time-locked to articles (Model 1), cloze probability was contrasted between-sentences, as opposed to between expected and unexpected sentence conditions. This is because, prior to the article, the sentence contexts were identical. The likely continuation (the expected article cloze value for that sentence) was taken as the cloze metric for both versions of the sentence (See *Table 2* for an example). In contrast, when measuring SPP effects time-locked to the nouns, the original noun cloze values for both expected and unexpected continuations were applied because the sentences arguably differed once participants had been exposed to the article variation.

The model effects were plotted using the *ggplot2* package (Wickham, 2016), with 83% confidence intervals to enable visual identification of statistical effects. For plots in which variables are presented dichotomously (e.g., high/low), this distinction was categorised according to the first and third quartiles.

Exploratory surprisal analyses

Early ERP grand average plots revealed event-related differences according to between-sentence cloze probability at earlier stages of the sentence (See *Figure 2*). This sparked interest regarding the accumulation of predictions over time, and of how the predictability of the prior words in the sentence may influence later predictions. Additional exploratory LMMs were thus included to analyse whether the surprisal of the preceding words interacted with the surprisal of the articles to influence ERP amplitudes. The raw surprisal values of the two preceding words (article-2 and article-1) and of the critical articles were included in the statistical models. To maintain consistency with our cloze models, LMMs were also computed investigating the effect of article/noun surprisal alone on ERP amplitude (See *Table 4* for exploratory model structures). IAF and the 1/f slope were included in all exploratory statistical models, and random effects were structured similarly to the original models. Note that although we ran SPP models with surprisal, the results either did not differ to those of cloze or did not reveal interactions with the surprisal of the critical word. Therefore, for simplicity's sake, we do not report the results of these models or specify their structures in *Table 4*, although the model outputs are presented in *Appendix 3*. Additionally, because an N400 effect at the noun could

not directly provide evidence for phonological prediction in the same manner as effects at the article (where a relationship between N400 amplitude and word predictability may index prediction for the upcoming noun), we did not deem it necessary to examine prior word surprisal in this context. Rather, analyses at the noun were primarily included as a sanity check. Therefore, to reduce complexity, we do not report N400 effects at the noun with prior word surprisal. Finally, Pearson correlations were calculated to examine the relationship between cloze probability and surprisal for the two respective word types.

Lexical surprisal was calculated using an open artificial intelligence model known as Generative Pre-Trained Transformer-2 (GPT-2; Radford et al., 2019) using the *Transformers* package in Python (Wolf et al., 2020). Surprisal in a linguistic context is calculated based on the probability of a given word in a linguistic corpus or database, whereby a higher surprisal value corresponds to lower predictability of a word within, for example, a sentence (Frank et al., 2013). GPT-2 is trained on a large corpus of English texts to traditionally predict upcoming words in a sentence, hence its efficacy in calculating surprisal (Radford et al., 2019). This measure was specifically used as the original experiment lacked cloze probability values of the prior words (Nieuwland et al., 2018).

Results

Statistical model outputs are presented in *Appendix 2.*

SPP effects

SPP ERP grand average plots time-locked to articles are shown in *Figure 2,* and ERP effects for nouns are shown in *Figure 3.* It was hypothesized that SPP amplitude would increase as word predictability increased, and that this relationship would be influenced by IAF and the 1/f slope. Model 1 was computed to test this hypothesis in relation to articles and did not detect a significant interaction between article cloze probability and IAF on SPP amplitude ($p = 0.748$, $\beta = -0.03$, $SE = 0.08$, 95% CI = -0.19 – 0.13). The effect of article cloze and 1/f slope was also nonsignificant ($p = 0.720$, $\beta = -0.03$, $SE = 0.08$, 95% CI = -0.19 – 0.13). Therefore, there were no detectable effects of cloze probability and individual factors on SPP activity time-locked to the articles.

Model 2 addressed the hypothesis that increases in noun cloze probability would lead to greater SPP ERP amplitudes, and that this would be modulated by IAF or the aperiodic 1/f slope. The model demonstrated a significant main effect of cloze probability on SPP amplitude ($p = 0.038$, $\beta = 0.11$, $SE = 0.05$, 95% CI = 0.01 – 0.21), such that increases in noun cloze probability were associated with decreased SPP amplitudes (see *Figure 4*). The interaction between cloze and IAF on SPP amplitude was non-significant ($p = 0.220$, $\beta = -0.05$, $SE = 0.04$, 95% CI = -0.12 – 0.03), similarly to the effect of cloze and 1/f slope ($p = 0.919$, $\beta = -0.00$, $SE = 0.04$, 95% CI = -0.08 – 0.07). As such, we did not detect a modulatory effect of individual factors on the relationship between cloze and the SPP.

N400 ERP effects

N400 grand average ERPs time-locked to articles are presented in *Figure 5.* To examine whether individual neural factors influence the relationship between cloze probability and N400 amplitude at the article, Model 3 was fitted. The model revealed a significant effect of cloze probability on N400 amplitude ($p <.001$, $\beta = -0.14$, $SE = 0.03$, 95% CI = -0.20 – -0.07), such that as cloze probability increased, N400 amplitude increased. The interaction between cloze and IAF was nonsignificant ($p = 0.937$, $\beta = 0.00$, $SE = 0.03$, 95% CI = -0.06– 0.07), as

was the interaction between cloze and 1/f slope (p = 0.512, β = -0.02, SE = 0.03, 95% CI = -0.09 – 0.04).

The effect of cloze probability, IAF and 1/f slope on N400 amplitude time-locked to nouns was explored in Model 4. The model detected a significant main effect of cloze probability on N400 amplitude (p <.001, β = 0.71, SE = 0.07, 95% CI = 0.56 – 0.85), where increases in cloze probability were associated with decreased N400 amplitudes. The interaction between cloze and IAF on N400 amplitude did not reach significance (p = 0.395, β = -0.03, SE = 0.04, 95% CI = -0.11 – 0.04). The effect of cloze and 1/f slope was also nonsignificant (p = 0.127, β = 0.06, SE = 0.04, 95% CI = -0.02 – 0.13). Therefore, whilst cloze probability influenced N400 amplitudes following the articles and nouns, this relationship was not modulated by individual factors.

Results of models with surprisal

As described above, whilst we ran SPP models with surprisal, the results either yielded the same outcomes as the cloze probability models or did not reveal interactions with the surprisal of the critical word. Therefore, for simplicity's sake, the models are not reported here although the outputs are presented in *Appendix 3*.

Grand average N400 ERPs according to article surprisal are presented in *Figure 7,* whilst grand averages according to noun surprisal are shown in *Figure 8.* To determine whether article surprisal influenced N400 amplitude, Model 5 was computed. The interaction between article surprisal and IAF on N400 amplitude was nonsignificant (p = 0.557, β = -0.02, SE = 0.04, 95% CI = -0.09 – 0.05). The effect of article surprisal and 1/f slope also did not reach significance (p = 0.671, β = -0.02, SE = 0.04, 95% CI = -0.09 – 0.06). Therefore, article surprisal, IAF and 1/f slope did not interact to influence the amplitude of the N400 component.

To investigate the role of prior surprisal in prediction, Model 6a was fitted with article, a-1 and a-2 surprisal, and the 1/f slope. A significant interaction effect between article surprisal, a-1 surprisal and a-2 surprisal was detected (p = 0.035, β = 0.11, SE = 0.05, 95% CI = 0.01 – 0.22). In most cases, increases in article surprisal were associated with increasing N400 amplitudes. However, this relationship was not observed when a-2 and a-1 surprisal were low (See *Figure 9a*). Model 6b predicted N400 amplitude from article, a-1 and a-2 surprisal, and IAF, which led to a significant interaction between article surprisal, a-2 surprisal and IAF (p = 0.045, β = -0.07, SE = 0.04, 95% CI = -0.15 – -0.00). Whilst increases in article surprisal were associated with increases in N400 amplitude, this relationship was strongest for high IAF individuals when a-2 surprisal was high (See *Figure 9b*).

The effect of noun surprisal on N400 amplitude was investigated via Model 7. A significant main effect of noun surprisal was observed (p <.001, β = -0.79, SE = 0.12, 95% CI = -1.03 – -0.55), such that greater noun surprisal values were associated with larger N400 amplitudes.

Correlational models

Shapiro-wilk tests revealed that article cloze probability and article surprisal were not normally distributed, and as such, a Spearman correlation was computed to examine the relationship between the two variables. The test revealed a significant but weak correlation (r(158) = -.25, p = 0.001), such that increases in article cloze were associated with decreases in article surprisal (see *Figure 10a*). A second Spearman correlation was calculated to determine the relationship between noun surprisal and noun cloze probability, after Shapiro-wilk tests revealed that both variables also did not conform to a normal distribution. Noun surprisal and noun cloze

probability were significantly negatively correlated ($r(157) = -.63$, $p < .001$), with increases in noun cloze associated with decreases in noun surprisal (see *Figure 10b*). Finally, we examined the correlation between the 1/f slope and IAF using a Spearman correlation, as these variables were not normally distributed. The test revealed a significant but weak negative correlation between the two variables ($r(310) = -.17$, $p < .01$), such that increases in IAF were associated with decreased (flatter) 1/f slopes.

Discussion

The present study sought to investigate the degree to which prediction underlies linguistic processing via an analysis of individual neural differences and ERP activity in the Nieuwland et al. (2018) data. Our analysis did not reveal a positive relationship between word predictability and the magnitude of the SPP as was hypothesized. This may question the extent to which the SPP reflects prediction during natural language processing. Initial N400 models time-locked to articles demonstrated increases in N400 amplitude as cloze probability increased, whilst article surprisal and N400 amplitude were not significantly related. At a first glance, this may be taken to suggest that the brain does not predict the phonological form of an upcoming noun, in line with Nieuwland and colleagues' original findings. However, evidence for prediction arose when prior surprisal was considered, such that N400 amplitudes increased as article surprisal increased. This relationship was not observed when the surprisal of the two prior words was low but was strengthened for high IAF individuals when article-2 surprisal was high. Broadly, our reanalysis contributes novel insights to the debate surrounding prediction in language, by suggesting that prediction during linguistic comprehension depends on contextual and individual factors. This emphasises the adaptive and between-subject nature of prediction, whilst highlighting the variability that surrounds predictive processing at the article.

The SPP may be a limited index of prediction during natural language processing

It was hypothesized that SPP amplitudes would increase as words became more predictable, reflecting anticipatory processing during linguistic comprehension. However, our analyses in the pre-stimulus window did not reveal a significant effect of article cloze probability on SPP amplitude, whilst SPP amplitudes preceding the nouns decreased as cloze probability increased. These findings are inconsistent with prior literature, which demonstrates a positive relationship between the magnitude of the SPP/SPN and word predictability (Grisoni et al., 2017, 2021; León-Cabrera et al., 2017, 2019). Whilst at face level, these findings might be taken to suggest that participants were not predicting upcoming semantic information, the results may be further illuminated by considering paradigm-specific effects.

As the SPP is proposed to reflect the prediction of semantic information (Grisoni et al., 2021; Pulvermüller & Grisoni, 2020), the observed null article finding may be explained by the overlap in meaning between the articles 'a' and 'an,' resulting in a similar semantic prediction between the two. Alternatively, the noun effect may suggest that SPP analyses were influenced by the temporal overlap between the pre-stimulus and N400 windows following the prior words. Most studies observing SPP/SPN effects employed intervals preceding the critical words of 1000ms or longer to capture activity independent of ERP components following the prior word (Grisoni et al., 2017, 2021; León-Cabrera et al., 2017, 2019). In contrast, the present study included interstimulus intervals of 300ms, which overlapped with the prior word's N400 window. To test whether the N400 following the prior words was probed in our SPP analyses, we also ran the SPP models whilst controlling for prior word surprisal (for model outputs, see

Appendix 3). This did not influence the results, likely because whilst the windows for the two components overlapped, the topographies differed (frontal for the SPP and centroparietal for the N400). Further, the relationship between critical word predictability (as measured by both cloze and surprisal) and SPP amplitude was not influenced by prior word surprisal or individual factors. This is in contrast with the N400 patterns at the article, which may provide evidence for probabilistic prediction under certain circumstances. Therefore, as an SPP effect in the expected direction was absent even after including factors that influenced prediction (as evidenced by the N400 effects), this may suggest that the SPP does not reflect naturalistic linguistic prediction. This raises the question of whether the longer intervals in other studies encourage prediction to a greater extent, or whether they give rise to a process that differs from natural language comprehension – an interesting question for future research. Ultimately, while we sought to gauge prediction more directly via an analysis of the SPP, effects relating to the N400 may contribute more strongly to understandings of predictive processing in language.

N400 effects at the article are variable and offer mixed results for prediction

Initial article analyses revealed increases in the N400 as cloze probability increased, questioning the extent to which the brain predicts upcoming linguistic information. This result opposes both DeLong et al. (2005), who found the reversed effect, and Nieuwland et al. (2018), whose N400-article analysis did not reach significance (although the trend was detected in some laboratories in Nieuwland and colleagues' replication analysis). Differences in the data analysis pipeline between our analysis and Nieuwland et al.'s (2018) study may have contributed to the differential results. Variations in pre-processing steps and our inclusion of pre-stimulus activity as a model covariate (which is shown to improve statistical power over baseline correction; Alday, 2019), may provide a potential explanation for this outcome. Although unexpected, this finding may also stem from the use of cloze probability, which may differ from surprisal in its ability to gauge the predictability of function words such as articles.

When surprisal was used to operationalize word predictability as opposed to cloze probability, the N400 effect no longer reached significance. This is in line with Nieuwland and colleagues' original analysis, suggesting that phonological prediction in language may be limited. On the other hand, it is inconsistent with Yan et al.'s (2017) reanalysis of Nieuwland et al. (2018), which revealed increases in the N400 as article surprisal increased (supporting phonological prediction in language). However, whilst we calculated surprisal using corpus-derived GPT-2 models, Yan and colleagues (2017) used the log-transformation of cloze as a measure of surprisal. Consequently, the mixed results at the article may in part arise from the use of differential word predictability metrics; a suggestion that is supported by the weak negative correlation between article cloze probability and surprisal observed in the present analysis. Cloze probability and GPT-2 measures appear to model N400 patterns slightly differently, particularly at the lower end of the predictability spectrum (Szewczyk & Federmeier, 2022). Whilst cloze is limited in modelling N400 effects to unexpected words with cloze probabilities closer to zero, GPT-2 measures may explain more variance in N400 amplitudes here due to their reliance on the log scale (Szewczyk & Federmeier, 2022). Other research however suggests that cloze probability is a better predictor of N400 amplitude than GPT-2 surprisal (Michaelov et al., 2022). Interestingly, all noun analyses revealed a consistent effect in the typical direction (similarly to DeLong et al., 2005 and Nieuwland et al., 2018), and noun cloze probability and noun surprisal were strongly negatively related (in line with theory; Pickering & Gambi, 2018). This may also suggest that the predictability of function words such as articles is more difficult to gauge, potentially because such words are not as semantically rich as content words (e.g., nouns). Whilst semantic information accumulates across a sentence to constrain subsequent word choices, early speech sounds do not strongly limit later word possibilities,

which may render predictability measurements difficult (Huettig et al., 2022). Therefore, whilst the present N400 results at a superficial level appear to provide evidence against phonological prediction, the diversity in outcomes at the article underscores the substantial variability that may surround the processing of this word. This is further emphasised by the observation that the relationship between article surprisal and N400 amplitude appears subject to individual and contextual variation.

Predictive processing depends on prior contextual information

While the above results may question the extent of prediction in language, the analyses including prior word surprisal suggest that predictive processing depends on prior context. When the surprisal of the two preceding words in the sentence was included in the statistical models, increases in article surprisal were associated with increases in N400 amplitude (in line with DeLong et al., 2005). However, this effect was not present when the surprisal of the two prior words was low, suggesting that the N400 is sensitive to prior contextual information; a notion that is broadly compatible with past research (Boudewyn et al., 2015; Fleur et al., 2020; Freunberger & Roehm, 2017; Maess et al., 2016; Ness & Meltzer-Asscher, 2018; Szewczyk & Wodniecka, 2020; Szewczyk et al., 2020). This result may thus indicate that participants were predicting the phonological characteristics of the following noun, although only under certain circumstances. Nevertheless, it offers stronger support for the N400 as reflecting prediction versus integration. The shared semantic meaning of 'a/an' in this context should not cause challenges in semantic integration and, consequently, should not result in an N400 effect akin to the one observed in the present study (DeLong et al., 2005). Whilst this may thus support prediction perspectives of the N400, the absence of an effect in cases of low prior word surprisal might be taken to suggest that participants were not predicting under such circumstances. At a first glance, this result appears somewhat counterintuitive: shouldn't predictions theoretically be strongest in this case, given that prior context provides converging support for the current predictive model?

An alternative explanation for this effect may stem from the notion that the N400 reflects a precision-weighted prediction error signal (Bornkessel-Schlesewsky & Schlesewsky, 2019), with precision reflecting the amount of certainty (or inverse of variance) in the data (Feldman & Friston, 2010; Friston, 2005). According to Bayesian frameworks, precision influences the relative weightings of the sensory input vis-à-vis the prior belief, which has consequences for predictive model updating (Adams et al., 2013). In the present study, low prior word surprisal may have fostered highly precise predictions, thereby concomitantly decreasing the precision attributed to the article such that it was deemed irrelevant for hypothesis testing. This may have consequently resulted in weaker N400 amplitudes as prediction errors at the article were 'ignored' in favour of predictions. The potential for articles to be overlooked is compatible with prior eye-tracking findings, where shorter words are typically skipped more frequently than longer words (Slattery & Yates, 2018), with highly common two-letter words being skipped by skilled readers at a rate of approximately 75% during reading (Leinenger & Rayner, 2017; Rayner & McConkie, 1976 in Faber et al., 2020). Further, whilst word skipping is also influenced by predictability, such that highly predictable words are more likely to be skipped (e.g., Balota et al., 1985; Ehrlich & Rayner, 1981; Slattery & Yates, 2018), these effects appear to differ for articles. For example, Angele and Rayner (2013) presented participants with a preview of the article 'the' in parafoveal vision, in a manner that rendered it syntactically anomalous given the prior sentence context. Participants tended to skip the preview despite its poor fit with the sentence, suggesting that the anomalous article was overlooked. Taken together, these findings may suggest that articles are frequently skipped, even when unpredictable. Furthermore, readers with greater print exposure and spelling ability have been

shown to skip words more frequently (Faber et al., 2020; Slattery & Yates, 2018), highlighting the role of individual variability in this relationship. Therefore, even though results from natural reading are, of course, not directly comparable to the word-by-word presentation employed in the present experiment, it appears possible that article-induced prediction errors were not considered here under conditions of high prior predictability, analogous to the article skipping findings. In addition to providing a potential explanation for the reduced N400 amplitudes that we observed, this notion is compatible with active inference theories, which propose that prediction error is not only reduced via changes to one's predictive model, but through active sampling of the sensory environment in accordance with one's hypothesis (Friston et al., 2016; Friston & Frith, 2015; Parr et al., 2022). As such, comprehenders may at times neglect unexpected articles in favour of a top-down expectation.

Ultimately, the present results, in addition to the mixed findings regarding cloze and surprisal described above, point towards a uniqueness within the article that gives rise to significant variability, and which may question the utility of this and similar paradigms. If information at the article is overlooked under certain circumstances, and if the relative weighting of the bottom-up versus top-down information influences the N400, interpretations from such paradigms may be more complicated than initially assumed. Interestingly, this could also suggest that the original appeal of Delong et al.'s (2005) design – that the article does not contain rich lexical-semantic content of its own – may simultaneously be its greatest weakness. In further support of the variability surrounding the article is the observation that this relationship was influenced by IAF.

Individual alpha frequency (IAF) modulates predictive processing during language comprehension

In addition to effects of prior context, article N400 amplitudes were influenced by IAF, emphasising the subject-specific nature of prediction. Whilst the N400 amplitude increased with increasing article surprisal, this trend was strongest for high IAF individuals when article-2 surprisal was high. Therefore, it is possible to suggest that under conditions of uncertainty, high IAF individuals rely on prediction to a greater extent than low IAF individuals. Alternatively, and in line with our previous discussions concerning precision, this result may also imply that high IAF individuals were weighting the bottom-up information at the article more strongly (i.e., they were affording more precision to the article), resulting in stronger N400 effects. As high prior surprisal likely renders it difficult to form a precise prediction, such individuals may have prioritised the sensory input for model updating. This is supported by prior research, where those with a high IAF demonstrate faster information processing speeds, suggesting that they may sample the perceptual environment more rapidly (Klimesch et al., 1996; Samaha & Postle, 2015; Surwillo, 1961, 1963). Other research proposes that such individuals have a greater inclination towards predictive model updating (Kurthen et al., 2020), which may manifest in larger N400 amplitudes to surprising articles as observed here. Therefore, whilst N400 effects at the article are typically discussed as reflecting prediction for the upcoming noun, the components' ties to precision (Bornkessel-Schlesewsky & Schlesewsky, 2019) imply that high IAF individuals may adopt a more flexible model updating strategy during conditions of uncertainty. However, further research would be beneficial to determine whether IAF directly influences stimulus precision weightings, potentially by investigating correlates that index prediction errors for precision weightings themselves (e.g., the P300 ERP component, as suggested by Bornkessel-Schlesewsky, Alday, et al., 2022). Additionally, whilst IAF influenced N400 amplitudes, we did not detect any effects relating to the 1/f aperiodic slope. Although we investigated 1/f as a between-subjects (trait-like) measure, in line with prior research (e.g., Bornkessel-Schlesewsky et al., 2022; Demuru & Fraschini,

2020; Dziego et al., 2023; McSweeney et al., 2021; Voytek & Knight, 2015), the 1/f slope also shows state-like changes and has been linked with norepinephrine activity and phasic changes in neural gain (Pertermann et al., 2019; Rosenblum, 2023). Consequently, future research may benefit from examining 1/f on a trial-by-trial basis to determine whether changes relating to prediction may be more transient. Nevertheless, the present findings emphasise the role of IAF in predictive processing, and suggest that whilst prediction may be an inherent property of cognition (Friston, 2010), the extent to which information is used for predictive model updating is subject to inter-individual variability.

Conclusion

The present study sheds light on the adaptability of predictive processing, whilst emphasising the susceptibility of the N400 component to judgements concerning precision. Whilst we observed evidence for phonological linguistic prediction under certain circumstances, our results speak to the potential sources of variability that alter prediction tendencies at the article, implying that under conditions of high prior predictability, prediction errors at the article may be overlooked in favour of one's predictive model. This may explain how internal language models cope with change as an inherent property of language, as prior context may inform the extent to which subsequent information is used for predictive model updating. The role of IAF in this relationship also suggests that some individuals may be more likely to adjust their predictions than others, having implications for understandings of prediction as a fundamental cognitive mechanism.

Data availability statement

Nieuwland and colleagues' data used in the present analysis is publicly available at https://osf.io/eyzaq/, whilst our data analysis scripts to replicate this investigation are publicly available at https://osf.io/b7txn/.

Figures and tables

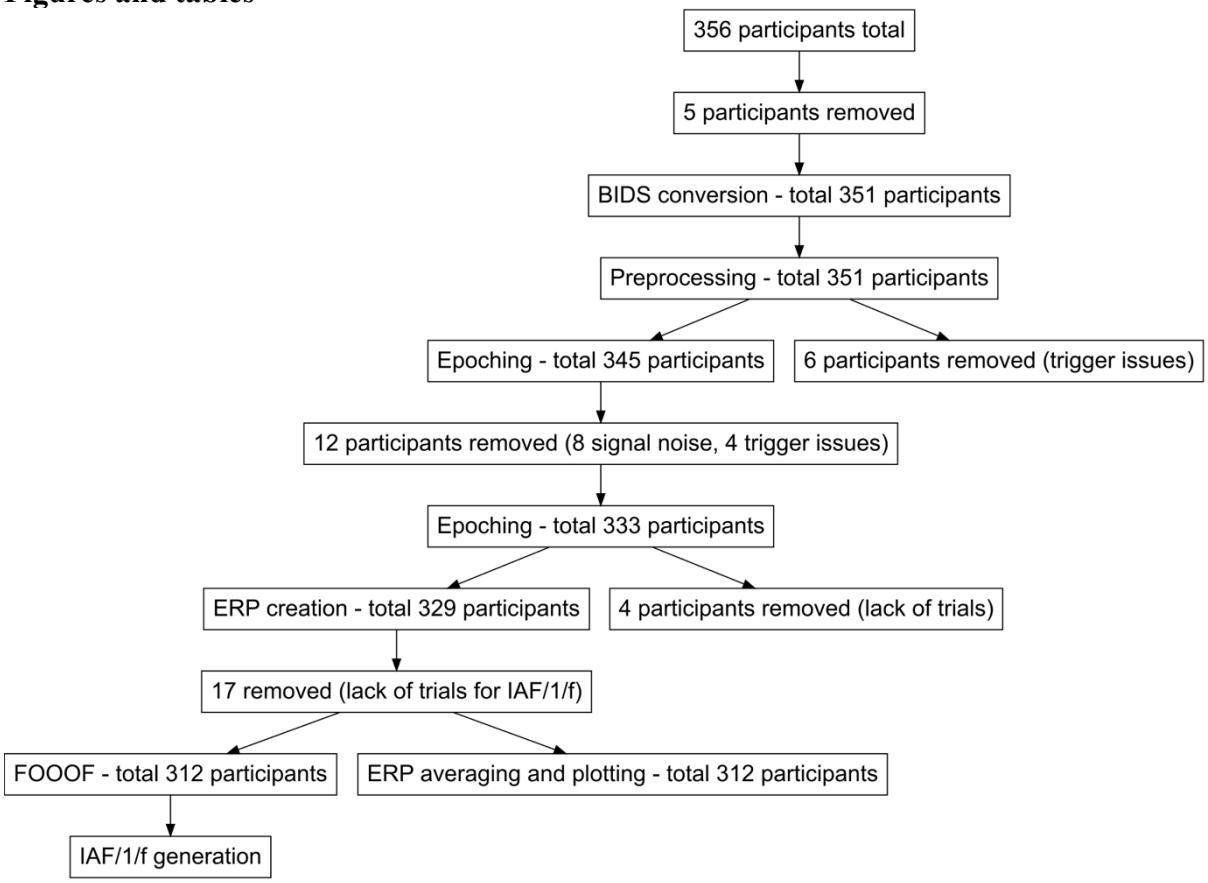

Figure 1.
The number of participants at each stage of the data analysis, including the number removed and reasons for removal.

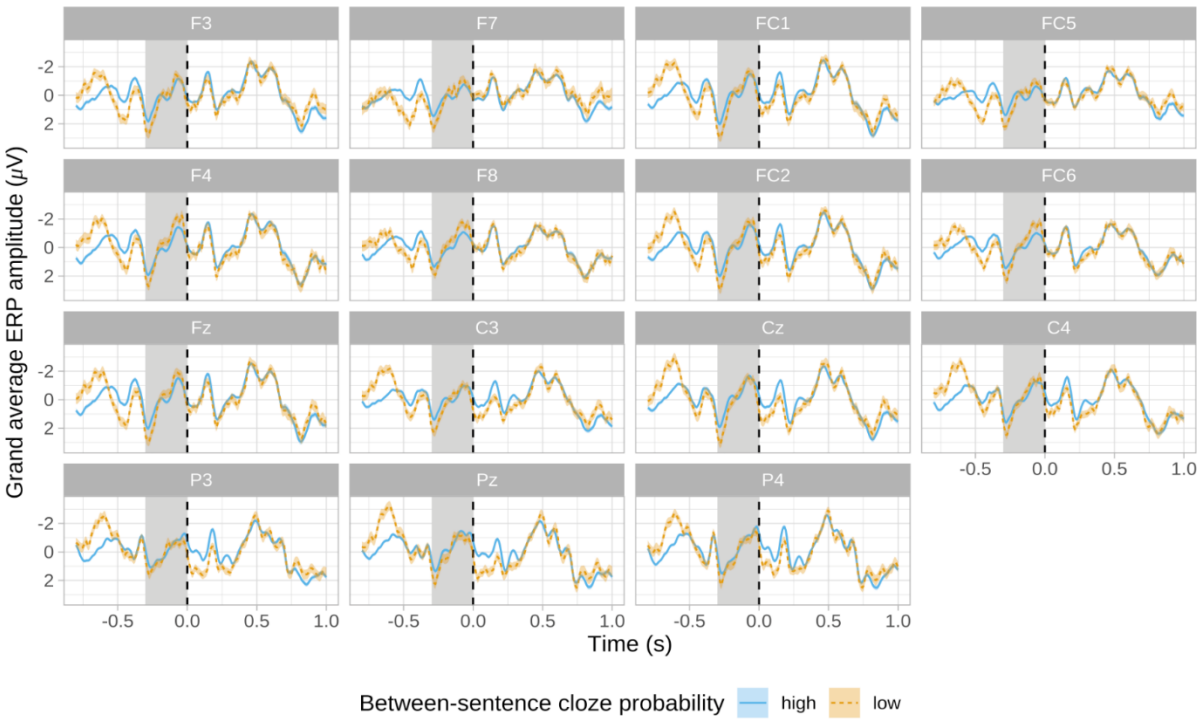

Figure 2.
SPP ERP grand average plots for articles over channels of interest according to cloze probability (n = 329). Blue lines represent high article cloze probability (>50%) whilst orange dashed lines reflect low article cloze probability (<50%). Note that between-sentence article cloze is plotted here to gauge SPP effects. Blue and orange shading reflects the standard errors for each condition. The SPP window is shaded grey, and the black dashed line depicts the onset of the article word. Note that the plot depicts non-baseline corrected ERP activity.

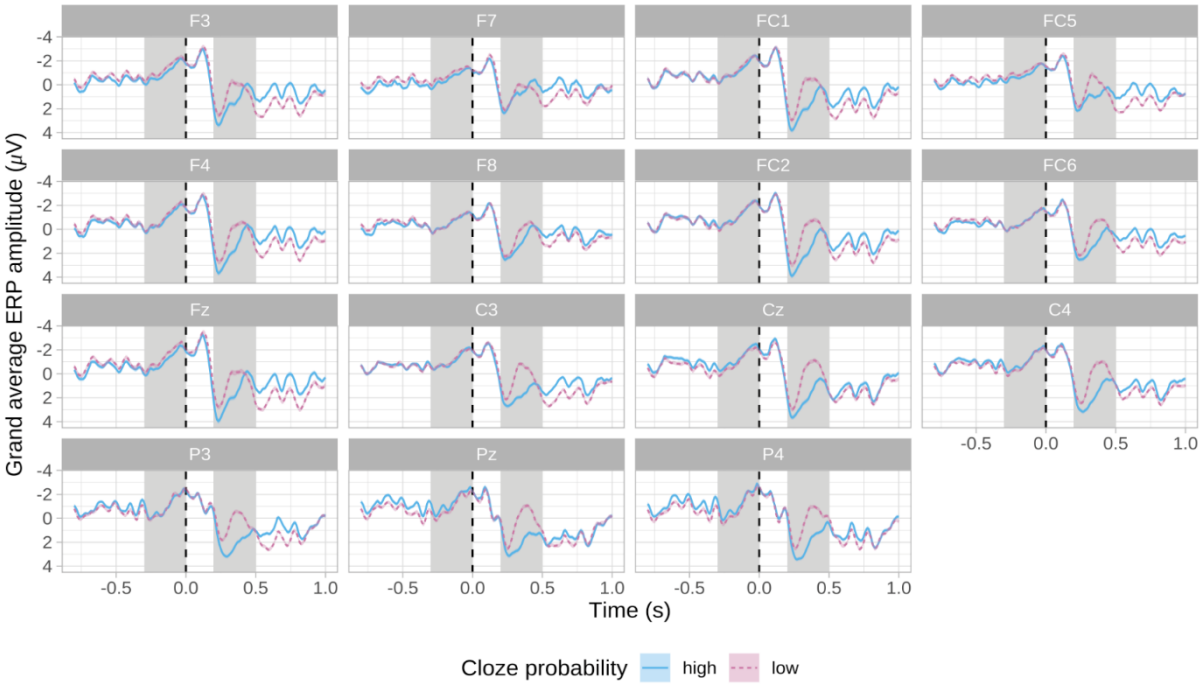

Figure 3.
Grand average ERP plots for noun words over channels of interest according to cloze probability (n = 329). Blue lines represent high noun cloze probability (>50) whilst magenta dashed lines reflect low noun cloze probability (<50). Blue and magenta shading reflects the standard errors for the respective conditions. The SPP window and the N400 window are denoted via grey shading, and the black dashed line depicts the onset of the noun word. Note that the plot depicts non-baseline corrected ERP activity.

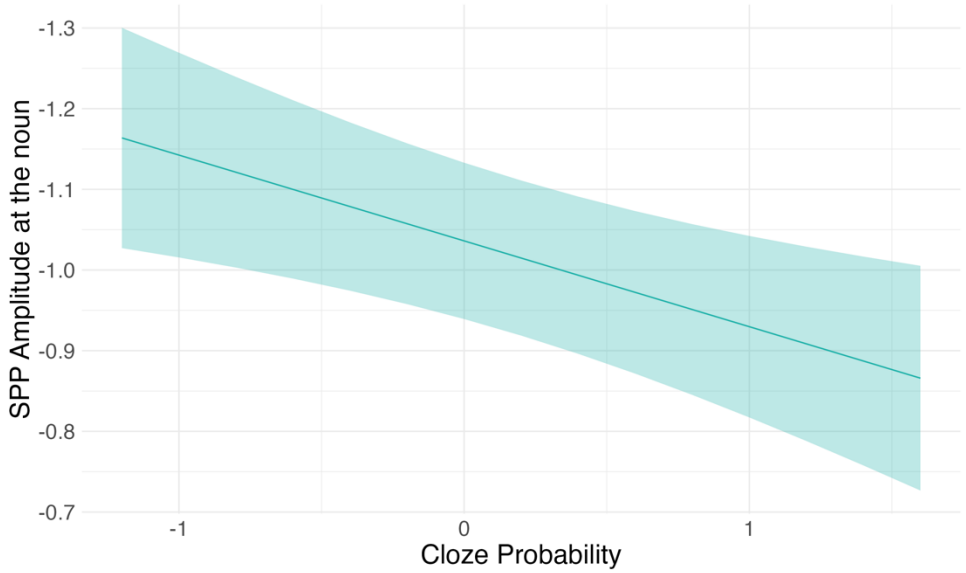

Figure 4.
Linear mixed model results depicting the effect of cloze probability on SPP amplitude, as modelled for nouns (p = 0.038, β = 0.11, SE = 0.05, 95% CI = 0.01 – 0.21). Lines represent model fit, with shading depicting the 83% confidence intervals.

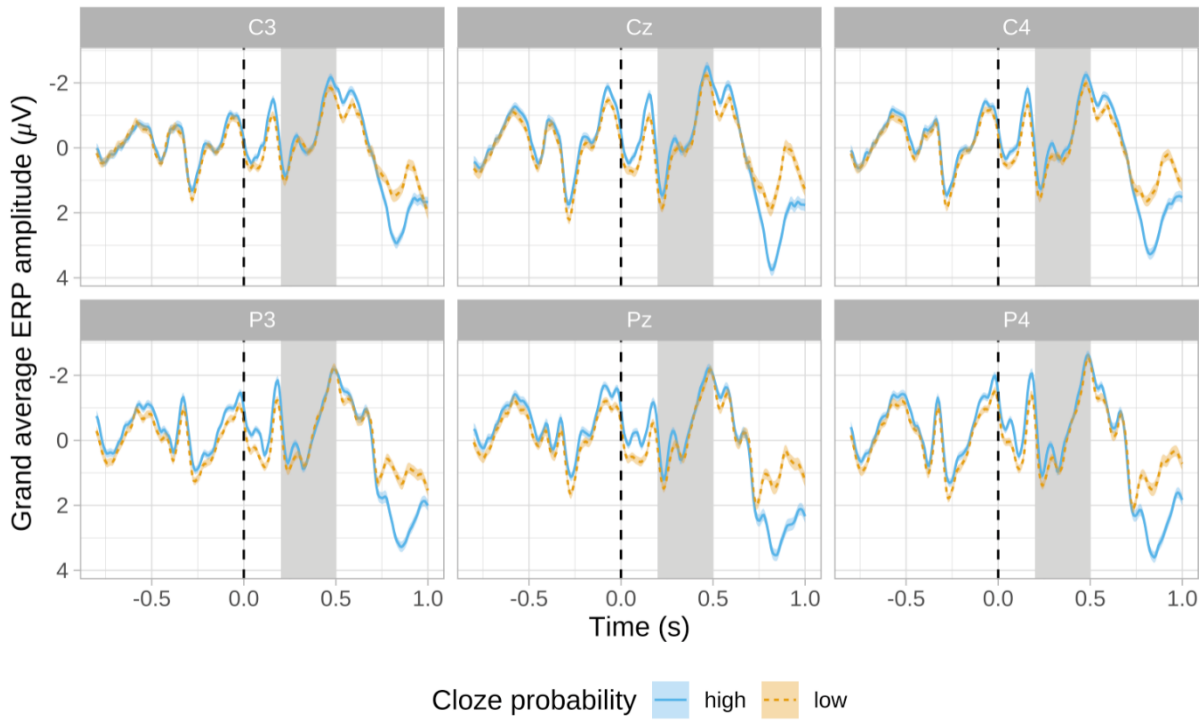

Figure 5.
Grand average ERP plots of N400 effects for articles over channels of interest, according to cloze probability (n = 329). Blue lines represent high cloze probability (>50) whilst orange dashed lines reflect low cloze probability (<50). Blue and orange shading depicts the standard errors for the two conditions. The N400 window is depicted via grey shading, and the black dashed line represents the onset of the article word. Note that the plot depicts non-baseline corrected ERP activity.

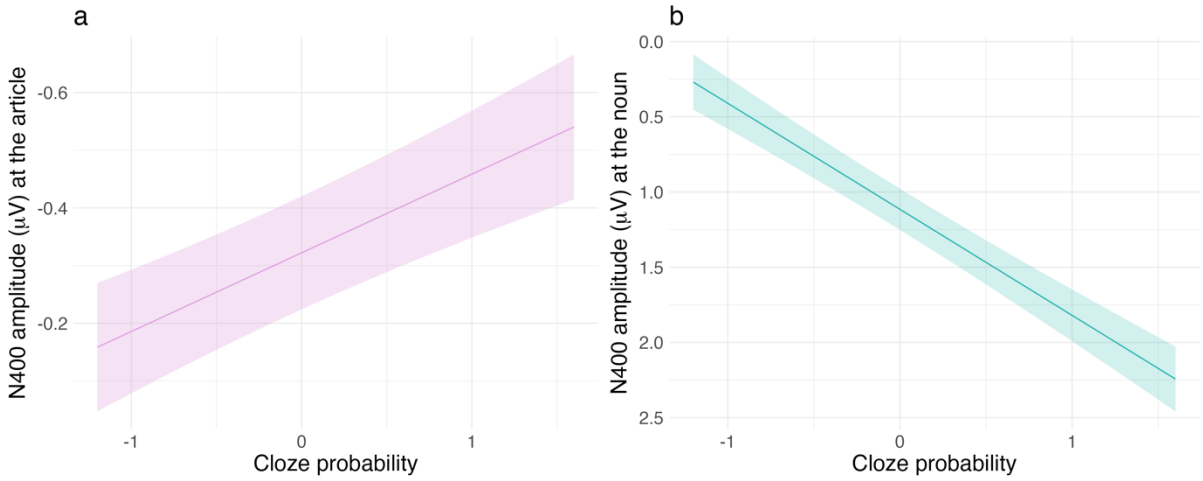

Figure 6. Linear mixed model results for N400 effects. **(a)** The effect of cloze probability on N400 amplitude time-locked to articles (p <.001, β = -0.14, SE = 0.03, 95% CI = -0.47 – -0.19). **(b)** The effect of cloze probability on N400 amplitude time-locked to nouns (p <.001, β = 0.71, SE = 0.07, 95% CI = 0.56 – 0.85). Shading in both plots reflects 83% confidence intervals and lines indicate model fit.

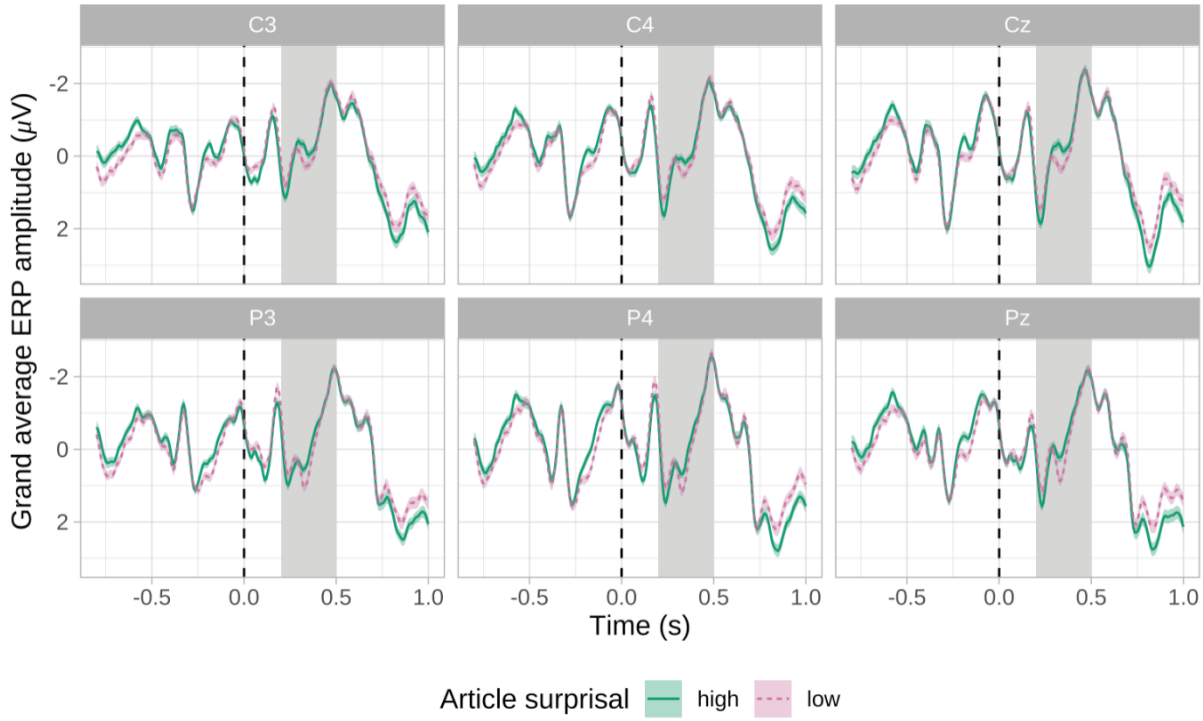

Figure 7.
Grand average N400 ERP plots for articles over channels of interest, according to surprisal (n = 329). Green lines represent high surprisal (>4.08; the mean article surprisal value) whilst magenta dashed lines reflect low surprisal (<4.08). Green and magenta shading depicts the standard errors for the two conditions. The N400 window is depicted via grey shading, and the black dashed line represents the onset of the article. Note that the plot depicts non-baseline corrected ERP activity.

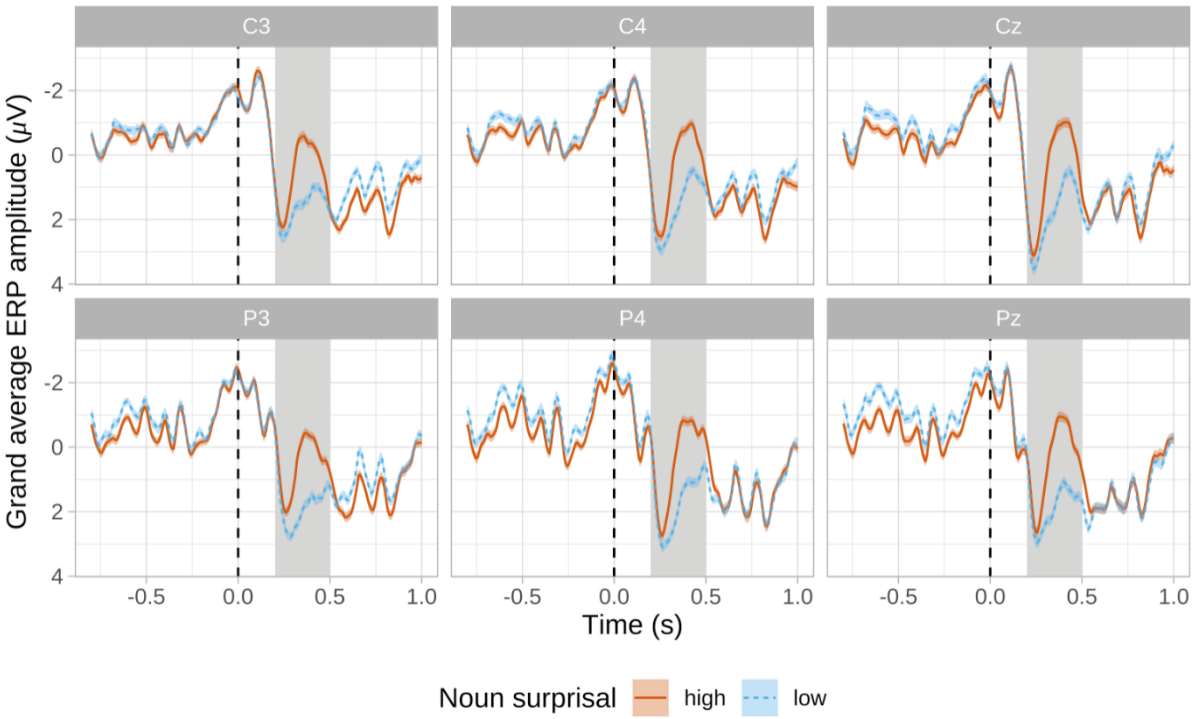

Figure 8.
Grand average N400 ERP plots for nouns over channels of interest, according to surprisal (*n* = 329). Red lines represent high surprisal (>5.8; the mean noun surprisal value) whilst blue dashed lines reflect low surprisal (<5.8). Red and blue shading depicts the standard errors for the two conditions. The N400 window is depicted via grey shading, and the black dashed line represents the onset of the noun. Note that the plot depicts non-baseline corrected ERP activity.

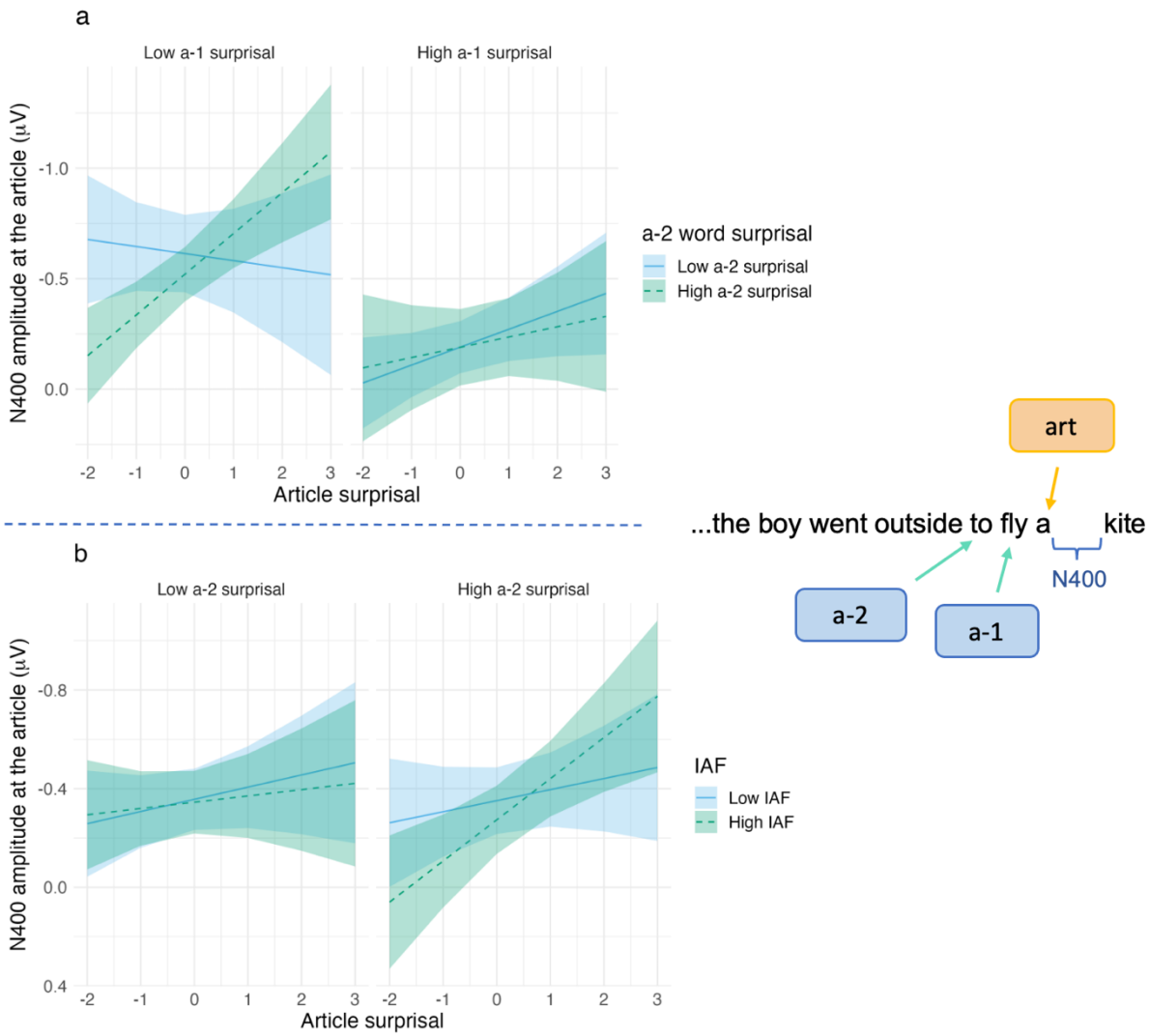

Figure 9. Linear mixed model results of article surprisal effects. **a)** N400 amplitude to articles, predicted by article–2 (a-2), article-1 (a-1), and article surprisal ($p = 0.035$, $\beta = 0.11$, $SE = 0.05$, 95% CI = 0.01 – 0.22). **(b)** N400 amplitude time-locked to articles, predicted article-2 (a-2) surprisal, article surprisal and IAF ($p = 0.045$, $\beta = -0.07$, $SE = 0.04$, 95% CI = -0.15 – -0.00). Shading in both plots reflects 83% confidence intervals, lines indicate model fit, and the dichotomisation of variables is for visualisation purposes only.

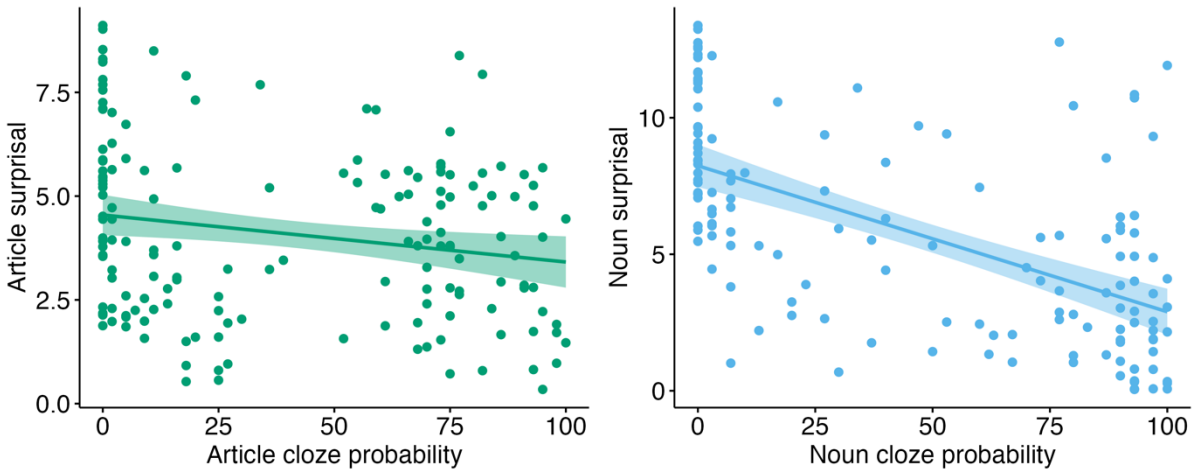

Figure 10. Spearman correlations depicting the relationship between cloze probability and surprisal. **(a)** The relationship between article cloze probability and article surprisal ($r(158) = -.25$, $p = 0.001$). **(b)** The relationship between noun cloze probability and noun surprisal ($r(157) = -.63$, $p < .001$).

Table 1.
Demonstrating the mean number of trials per condition that were entered into the ICA, with standard deviations (SD) in brackets.

Expected articles	Unexpected articles	Expected nouns	Unexpected nouns	Article-1*
39.97 (0.29)	39.98 (0.20)	39.97 (0.30)	38.96 (1.01)	79.98 (0.15)

**The article-1 window (-300 to 0ms preceding the word before the article) was used as a baseline period.*

Table 2. Example sentence demonstrating the cloze probability values (in brackets) for both the unexpected and expected continuations.
Note that prior to the article, the sentence versions are identical, thus justifying the application of the expected article cloze value (82) to all versions of the sentence when analysing pre-stimulus effects time-locked to articles.

Sentence beginning	**Expected article**	**Unexpected article**	**Expected noun**	**Unexpected noun**
The old wives' tale says that if you want to keep the doctor away then you should eat	an (82)	a (0)	apple (97)	carrot (0)

Table 3.
*Linear mixed-effects models for primary analyses with outcome variables, covariates, fixed and random effects. Note that IAF and 1/f were included as separate interaction terms, such that in model 1 for example, the interaction of cloze*IAF was examined independently from the interaction of cloze*1/f slope.*

Model	Outcome	Covariates	Fixed effects	Separate interaction terms	Random intercepts	Random slopes
1	**Pre-article** SPP amplitude (-300 to 0ms)	Article-1 word ERP amplitude (-300 to 0ms)	Between-sentence article cloze probability	1/f slope IAF	+ Subject + item	
2	**Pre-noun** SPP amplitude (-300 to 0ms)	Article-1 word ERP amplitude (-300 to 0ms)	Noun cloze probability	1/f slope IAF	+ Subject + item	By-subject and by-item according to cloze
3	**Post-article** N400 amplitude (200 to 500ms)	Pre-article ERP amplitude (-300 to 0ms)	Article cloze probability	1/f slope IAF	+ Subject + item	
4	**Post-noun** N400 amplitude (200 to 500ms)	Pre-noun ERP amplitude (-300 to 0ms)	Noun cloze probability	1/f slope IAF	+ Subject + item	By-subject and by-item according to cloze

Table 4.
Exploratory linear mixed-effects model structures with outcome variables, covariates, fixed and random effects.

Model	Outcome	Covariates	Fixed effects	Separate interaction terms	Random intercepts	Random slopes
5	**Post-article** N400 amplitude (200 to 500ms)	Pre-article ERP amplitude	Article surprisal	IAF 1/f	+ Subject + item	By-subject and by-item according to article surprisal
6a	**Post-article** N400 amplitude (200 to 500ms)	Pre-article ERP amplitude	Article surprisal Article-1 surprisal Article-2 surprisal 1/f		+ Subject + item	By-subject and by-item according to article surprisal
6b	**Post-article** N400 amplitude (200 to 500ms)	Pre-article ERP amplitude	Article surprisal Article-1 surprisal Article-2 surprisal IAF		+ Subject + item	By-subject and by-item according to article surprisal
7	**Post-noun** N400 amplitude (200 to 500ms)	Pre-noun ERP amplitude	Noun surprisal	IAF 1/f	+ Subject + item	By-subject and by-item according to noun surprisal

Reference list

Adams, R., Stephan, K., Brown, H., Frith, C., & Friston, K. (2013). The Computational Anatomy of Psychosis. *Frontiers in Psychiatry*, *4*. https://www.frontiersin.org/articles/10.3389/fpsyt.2013.00047

Alday, P. M. (2019). How much baseline correction do we need in ERP research? Extended GLM model can replace baseline correction while lifting its limits. *Psychophysiology*, *56*(12), e13451. https://doi.org/10.1111/psyp.13451

Angele, B., & Rayner, K. (2013). Processing *the* in the parafovea: Are articles skipped automatically? *Journal of Experimental Psychology: Learning, Memory, and Cognition, 39*(2), 649–662. https://doi.org/10.1037/a0029294

Appelhoff, S., Sanderson, M., Brooks, T. L., Vliet, M. van, Quentin, R., Holdgraf, C., Chaumon, M., Mikulan, E., Tavabi, K., Höchenberger, R., Welke, D., Brunner, C., Rockhill, A. P., Larson, E., Gramfort, A., & Jas, M. (2019). MNE-BIDS: Organizing electrophysiological data into the BIDS format and facilitating their analysis. *Journal of Open Source Software*, *4*(44), 1896. https://doi.org/10.21105/joss.01896

Apps, M. A. J., & Tsakiris, M. (2014). The free-energy self: A predictive coding account of self-recognition. *Neuroscience & Biobehavioral Reviews*, *41*, 85–97. https://doi.org/10.1016/j.neubiorev.

Balota, D. A., Pollatsek, A., & Rayner, K. (1985). The interaction of contextual constraints and parafoveal visual information in reading. *Cognitive Psychology*, *17*(3), 364–390. https://doi.org/10.1016/0010-0285(85)90013-1

Bar, M. (2011). *Predictions in the Brain*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195395518.001.0001

Bates, D., Kliegl, R., Vasishth, S., & Baayen, H. (2018). Parsimonious Mixed Models. *arXiv:1506.04967 [Stat]*. http://arxiv.org/abs/1506.04967

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software*, *67*, 1–48. https://doi.org/10.18637/jss.v067.i01

Bornkessel-Schlesewsky, I., Alday, P. M., Corcoran, A. W., Wilkinson, E. M., Sharrad, I., Kliegl, R., Lewis, R. L., Small, S. L., & Schlesewsky, M. (2022). *Effects of neural noise on predictive model updating across the adult lifespan* [Preprint]. Neuroscience. https://doi.org/10.1101/2022.12.14.520501

Bornkessel-Schlesewsky, I., Sharrad, I., Howlett, C. A., Alday, P. M., Corcoran, A. W., Bellan, V., Wilkinson, E., Kliegl, R., Lewis, R. L., Small, S. L., & Schlesewsky, M. (2022). Rapid adaptation of predictive models during language comprehension: Aperiodic EEG slope, individual alpha frequency and idea density modulate individual differences in real-time model updating. *Frontiers in Psychology*, *13*, 1–28. https://doi.org/10.3389/fpsyg.2022.817516

Bornkessel-Schlesewsky, I., & Schlesewsky, M. (2019). Toward a neurobiologically plausible model of language-related, negative event-related potentials. *Frontiers in Psychology*, *10*(298), 1–17. https://doi.org/10.3389/fpsyg.2019.00298

Boudewyn, M. A., Long, D. L., & Swaab, T. Y. (2015). Graded expectations: Predictive processing and the adjustment of expectations during spoken language comprehension. *Cognitive, Affective, & Behavioral Neuroscience*, *15*(3), 607–624. https://doi.org/10.3758/s13415-015-0340-0

Brown, C., & Hagoort, P. (1993). The Processing Nature of the N400: Evidence from Masked Priming. *Journal of Cognitive Neuroscience*, *5*(1), 34–44. https://doi.org/10.1162/jocn.1993.5.1.34

Brunia, C. H. M., Hackley, S. A., van Boxtel, G. J. M., Kotani, Y., & Ohgami, Y. (2011). Waiting to perceive: Reward or punishment? *Clinical Neurophysiology*, *122*(5), 858–868. https://doi.org/10.1016/j.clinph.2010.12.039

Chwilla, D. J., & Kolk, H. H. J. (2000). *Mediated Priming in the Lexical Decision Task: Evidence from Event-Related Potentials and Reaction Time*. *42*(3), 314-341. https://doi.org/10.1006/jmla.1999.2680

Clark, A. (2013). Whatever next? Predictive brains, situated agents, and the future of cognitive science. *Behavioral and Brain Sciences*, *36*(3), 181–204. https://doi.org/10.1017/S0140525X12000477

Corcoran, A. W., Alday, P. M., Schlesewsky, M., & Bornkessel-Schlesewsky, I. (2018). Toward a reliable, automated method of individual alpha frequency (IAF) quantification. *Psychophysiology*, *55*(7), e13064. https://doi.org/10.1111/psyp.13064

Cross, Z. R., Corcoran, A. W., Schlesewsky, M., Kohler, M. J., & Bornkessel-Schlesewsky, I. (2022). Oscillatory and Aperiodic Neural Activity Jointly Predict Language Learning. *Journal of Cognitive Neuroscience*, 1–20. https://doi.org/10.1162/jocn_a_01878

Dave, S., Brothers, T. A., & Swaab, T. Y. (2018). 1/f neural noise and electrophysiological indices of contextual prediction in aging. *Brain Research*, *1691*, 34–43. https://doi.org/10.1016/j.brainres.2018.04.007

DeLong, K. A., Urbach, T. P., & Kutas, M. (2005). Probabilistic word pre-activation during language comprehension inferred from electrical brain activity. *Nature Neuroscience*, *8*(8), Article 8. https://doi.org/10.1038/nn1504

Demuru, M., & Fraschini, M. (2020). EEG fingerprinting: Subject-specific signature based on the aperiodic component of power spectrum. *Computers in Biology and Medicine*, *120*, 103748. https://doi.org/10.1016/j.compbiomed.2020.103748

Donoghue, T., Dominguez, J., & Voytek, B. (2020). Electrophysiological Frequency Band Ratio Measures Conflate Periodic and Aperiodic Neural Activity. *BioRxiv*, 2020.01.11.900977. https://doi.org/10.1101/2020.01.11.900977

Dziego, C. A., Bornkessel-Schlesewsky, I., Jano, S., Chatburn, A., Schlesewsky, M., Immink, M. A., Sinha, R., Irons, J., Schmitt, M., Chen, S., & Cross, Z. R. (2023). Neural and cognitive correlates of performance in dynamic multi-modal settings. *Neuropsychologia*, *180*, 108483. https://doi.org/10.1016/j.neuropsychologia.2023.108483

Ehrlich, S. F., & Rayner, K. (1981). Contextual effects on word perception and eye movements during reading. *Journal of Verbal Learning and Verbal Behavior*, *20*(6), 641–655. https://doi.org/10.1016/S0022-5371(81)90220-6

Faber, M., Mak, M., & Willems, R. M. (2020). Word skipping as an indicator of individual reading style during literary reading. *Journal of Eye Movement Research*, *13*(3), 10.16910/jemr.13.3.2. https://doi.org/10.16910/jemr.13.3.2

Feldman, H., & Friston, K. J. (2010). Attention, Uncertainty, and Free-Energy. *Frontiers in Human Neuroscience*, *4*. https://doi.org/10.3389/fnhum.2010.00215

Ferreira, F., & Chantavarin, S. (2018). Integration and Prediction in Language Processing: A Synthesis of Old and New. *Current Directions in Psychological Science*, *27*(6), 443–448. https://doi.org/10.1177/0963721418794491

Fleur, D. S., Flecken, M., Rommers, J., & Nieuwland, M. S. (2020). Definitely saw it coming? The dual nature of the pre-nominal prediction effect. *Cognition*, *204*, 104335. https://doi.org/10.1016/j.cognition.2020.104335

Frank, S. L., Otten, L. J., Galli, G., & Vigliocco, G. (2013). Word surprisal predicts N400 amplitude during reading. *Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics.* https://repository.ubn.ru.nl/bitstream/handle/2066/119221/119221.pdf

Freunberger, D., & Roehm, D. (2017). The costs of being certain: Brain potential evidence for linguistic preactivation in sentence processing. *Psychophysiology*, *54*(6), 824–832. https://doi.org/10.1111/psyp.12848

Friston, K. (2005). A theory of cortical responses. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *360*(1456), 815–836. https://doi.org/10.1098/rstb.2005.1622

Friston, K. (2010). The free-energy principle: A unified brain theory? *Nature Reviews Neuroscience*, *11*(2). https://doi.org/10.1038/nrn2787

Friston, K., FitzGerald, T., Rigoli, F., Schwartenbeck, P., O'Doherty, J., & Pezzulo, G. (2016). Active inference and learning. *Neuroscience & Biobehavioral Reviews*, *68*, 862–879. https://doi.org/10.1016/j.neubiorev.2016.06.022

Friston, K. J., & Frith, C. D. (2015). Active inference, communication and hermeneutics. *Cortex*, *68*, 129–143. https://doi.org/10.1016/j.cortex.2015.03.025

Friston, K., & Kiebel, S. (2009). Predictive Coding under the Free-Energy Principle. *Philosophical Transactions: Biological Sciences*, *364*(1521), 1211–1221. https://doi.org/10.1098/rstb.2008.0300

Gramfort, A., Luessi, M., Larson, E., Engemann, D. A., Strohmeier, D., Brodbeck, C., Goj, R., Jas, M., Brooks, T., Parkkonen, L., & Hämäläinen, M. (2013). MEG and EEG data analysis with MNE-Python. *Frontiers in Neuroscience*, *7*(7), 267–267. https://doi.org/10.3389/fnins.2013.00267

Grandy, T. H., Werkle-Bergner, M., Chicherio, C., Lövdén, M., Schmiedek, F., & Lindenberger, U. (2013). Individual alpha peak frequency is related to latent factors of general cognitive abilities. *NeuroImage*, *79*, 10–18. https://doi.org/10.1016/j.neuroimage.2013.04.059

Grisoni, L., Dreyer, F. R., & Pulvermüller, F. (2016). Somatotopic Semantic Priming and Prediction in the Motor System. *Cerebral Cortex*, *26*(5), 2353–2366. https://doi.org/10.1093/cercor/bhw026

Grisoni, L., Miller, T. M., & Pulvermüller, F. (2017). Neural Correlates of Semantic Prediction and Resolution in Sentence Processing. *The Journal of Neuroscience*, *37*(18), 4848–4858. https://doi.org/10.1523/JNEUROSCI.2800-16.2017

Grisoni, L., Mohr, B., & Pulvermüller, F. (2019). Prediction mechanisms in motor and auditory areas and their role in sound perception and language understanding. *NeuroImage*, *199*, 206–216. https://doi.org/10.1016/j.neuroimage.2019.05.071

Grisoni, L., Tomasello, R., & Pulvermüller, F. (2021). Correlated Brain Indexes of Semantic Prediction and Prediction Error: Brain Localization and Category Specificity. *Cerebral Cortex*, *31*(3), 1553–1568. https://doi.org/10.1093/cercor/bhaa308

Hodapp, A., & Rabovsky, M. (2021). The N400 ERP component reflects an error-based implicit learning signal during language comprehension. *European Journal of Neuroscience*, *54*(9), 7125–7140. https://doi.org/10.1111/ejn.15462

Hohwy, J. (2013). *The Predictive Mind*. OUP Oxford.

Horga, G., Schatz, K. C., Abi-Dargham, A., & Peterson, B. S. (2014). Deficits in Predictive Coding Underlie Hallucinations in Schizophrenia. *Journal of Neuroscience*, *34*(24), 8072–8082. https://doi.org/10.1523/JNEUROSCI.0200-14.2014

Hosemann, J., Herrmann, A., Steinbach, M., Bornkessel-Schlesewsky, I., & Schlesewsky, M. (2013). Lexical prediction via forward models: N400 evidence from German Sign Language. *Neuropsychologia, 51*(11), 2224–2237. https://doi.org/10.1016/j.neuropsychologia.2013.07.013

Huettig, F., Audring, J., & Jackendoff, R. (2022). A parallel architecture perspective on pre-activation and prediction in language processing. *Cognition*, *224*, 105050. https://doi.org/10.1016/j.cognition.2022.105050

Immink, M. A., Cross, Z. R., Chatburn, A., Baumeister, J., Schlesewsky, M., & Bornkessel-Schlesewsky, I. (2021). Resting-state aperiodic neural dynamics predict individual differences in visuomotor performance and learning. *Human Movement Science*, *78*, 102829. https://doi.org/10.1016/j.humov.2021.102829

Ito, A., Martin, A. E., & Nieuwland, M. S. (2017). Why the A/AN prediction effect may be hard to replicate: A rebuttal to Delong, Urbach, and Kutas (2017). *Language, Cognition and Neuroscience*, *32*(8), 974–983. https://doi.org/10.1080/23273798.2017.1323112

Jas, M., Engemann, D., Raimondo, F., Bekhti, Y., & Gramfort, A. (2016). Automated rejection and repair of bad trials in MEG/EEG. *6th International Workshop on Pattern Recognition in Neuroimaging (PRNI)*. https://hal.archives-ouvertes.fr/hal-01313458

Kveraga, K., Ghuman, A. S., & Bar, M. (2007). Top-down predictions in the cognitive brain. *Brain and Cognition*, *65*(2), 145–168. https://doi.org/10.1016/j.bandc.2007.06.007

Kirschfeld, K. (2005). The physical basis of alpha waves in the electroencephalogram and the origin of the "Berger effect". *Biological Cybernetics*, *92*(3), 177–185. https://doi.org/10.1007/s00422-005-0547-1

Klimesch, W. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: A review and analysis. *Brain Research. Brain Research Reviews*, *29*(2–3), 169–195. https://doi.org/10.1016/s0165-0173(98)00056-3

Klimesch, W., Doppelmayr, M., Schimke, H., & Pachinger, T. (1996). Alpha Frequency, Reaction Time, and the Speed of Processing Information. *Journal of Clinical Neurophysiology*, *13*(6), 511–518.

Koster-Hale, J., & Saxe, R. (2013). Theory of Mind: A Neural Prediction Problem. *Neuron*, *79*(5), 836–848. https://doi.org/10.1016/j.neuron.2013.08.020

Kuperberg, G. R., & Jaeger, T. F. (2016). What do we mean by prediction in language comprehension? *Language, Cognition and Neuroscience*, *31*(1), 32–59. https://doi.org/10.1080/23273798.2015.1102299

Kurthen, I., Meyer, M., Schlesewsky, M., & Bornkessel-Schlesewsky, I. (2020). Individual Differences in Peripheral Hearing and Cognition Reveal Sentence Processing Differences in Healthy Older Adults. *Frontiers in Neuroscience*, *14*. https://doi.org/10.3389/fnins.2020.573513

Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest Package: Tests in Linear Mixed Effects Models. *Journal of Statistical Software*, *82*, 1–26. https://doi.org/10.18637/jss.v082.i13

León-Cabrera, P., Flores, A., Rodríguez-Fornells, A., & Morís, J. (2019). Ahead of time: Early sentence slow cortical modulations associated to semantic prediction. *NeuroImage*, *189*, 192–201. https://doi.org/10.1016/j.neuroimage.2019.01.005

León-Cabrera, P., Rodríguez-Fornells, A., & Morís, J. (2017). Electrophysiological correlates of semantic anticipation during speech comprehension. *Neuropsychologia*, *99*, 326–334. https://doi.org/10.1016/j.neuropsychologia.2017.02.026

Maess, B., Mamashli, F., Obleser, J., Helle, L., & Friederici, A. D. (2016). Prediction Signatures in the Brain: Semantic Pre-Activation during Language Comprehension. *Frontiers in Human Neuroscience*, *10*, 591–591. https://doi.org/10.3389/fnhum.2016.00591

Mantegna, F., Hintz, F., Ostarek, M., Alday, P. M., & Huettig, F. (2019). Distinguishing integration and prediction accounts of ERP N400 modulations in language processing

through experimental design. *Neuropsychologia*, *134*, 107199. https://doi.org/10.1016/j.neuropsychologia.2019.107199

McSweeney, M., Morales, S., Valadez, E. A., Buzzell, G. A., & Fox, N. A. (2021). Longitudinal age- and sex-related change in background aperiodic activity during early adolescence. *Developmental Cognitive Neuroscience*, *52*, 101035. https://doi.org/10.1016/j.dcn.2021.101035

Merkin, A., Sghirripa, S., Graetz, L., Smith, A. E., Hordacre, B., Harris, R., Pitcher, J., Semmler, J., Rogasch, N. C., & Goldsworthy, M. (2023). Do age-related differences in aperiodic neural activity explain differences in resting EEG alpha? *Neurobiology of Aging*, *121*, 78–87. https://doi.org/10.1016/j.neurobiolaging.2022.09.003

Michaelov, J. A., Coulson, S., & Bergen, B. K. (2022). So Cloze yet so Far: N400 Amplitude is Better Predicted by Distributional Information than Human Predictability Judgements. *IEEE Transactions on Cognitive and Developmental Systems*, 1–10. https://doi.org/10.1109/TCDS.2022.3176783

Morís, J., Luque, D., & Rodríguez-Fornells, A. (2013). Learning-induced modulations of the stimulus-preceding negativity. *Psychophysiology*, *50*(9), 931–939. https://doi.org/10.1111/psyp.12073

Ness, T., & Meltzer-Asscher, A. (2018). Predictive Pre-updating and Working Memory Capacity: Evidence from Event-related Potentials. *Journal of Cognitive Neuroscience*, *30*(12), 1916–1938. https://doi.org/10.1162/jocn_a_01322

Nieuwland, M. S., Politzer-Ahles, S., Heyselaar, E., Segaert, K., Darley, E., Kazanina, N., Von Grebmer Zu Wolfsthurn, S., Bartolozzi, F., Kogan, V., Ito, A., Mézière, D., Barr, D. J., Rousselet, G. A., Ferguson, H. J., Busch-Moreno, S., Fu, X., Tuomainen, J., Kulakova, E., Husband, E. M., … Huettig, F. (2018). Large-scale replication study reveals a limit on probabilistic prediction in language comprehension. *ELife*, *7*, e33468. https://doi.org/10.7554/eLife.33468

Ono, K., Hashimoto, J., Hiramoto, R., Sasaoka, T., & Yamawaki, S. (2021). Modulatory Effects of Prediction Accuracy on Electroencephalographic Brain Activity During Prediction. *Frontiers in Human Neuroscience*, *15*. https://doi.org/10.3389/fnhum.2021.630288

Ouyang, G., Hildebrandt, A., Schmitz, F., & Herrmann, C. S. (2020). Decomposing alpha and 1/f brain activities reveals their differential associations with cognitive processing speed. *NeuroImage*, *205*, 116304. https://doi.org/10.1016/j.neuroimage.2019.116304

Parr, T., Pezzulo, G., & Friston, K. J. (2022). *Active Inference: The Free Energy Principle in*

Mind, Brain, and Behavior. https://doi.org/10.7551/mitpress/12441.001.0001

Pathania, A., Euler, M. J., Clark, M., Cowan, R. L., Duff, K., & Lohse, K. R. (2022). Resting EEG spectral slopes are associated with age-related differences in information processing speed. *Biological Psychology*, *168*, 108261. https://doi.org/10.1016/j.biopsycho.2022.108261

Pertermann, M., Mückschel, M., Adelhöfer, N., Ziemssen, T., & Beste, C. (2019). On the interrelation of 1/f neural noise and norepinephrine system activity during motor response inhibition. *Journal of Neurophysiology*, *121*(5), 1633–1643. https://doi.org/10.1152/jn.00701.2018

Pickering, M. J., & Gambi, C. (2018). Predicting While Comprehending Language: A Theory and Review. *Psychological Bulletin*, *144*(10), 1002–1044. https://doi.org/10.1037/bul0000158

Press, C., Kok, P., & Yon, D. (2020). The Perceptual Prediction Paradox. *Trends in Cognitive Sciences*, *24*(1), 13–24. https://doi.org/10.1016/j.tics.2019.11.003

Pulvermüller, F., & Grisoni, L. (2020). Semantic Prediction in Brain and Mind. *Trends in Cognitive Sciences*, *24*(10), 781–784. https://doi.org/10.1016/j.tics.2020.07.002

Rabovsky, M., Hansen, S. S., & McClelland, J. L. (2018). Modelling the N400 brain potential as change in a probabilistic representation of meaning. *Nature Human Behaviour*, *2*(9), Article 9. https://doi.org/10.1038/s41562-018-0406-4

Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., & Sutskever, I. (2019). Language Models are Unsupervised Multitask Learners. *OpenAI blog*, *1*(8), 9.

Rao, R. P. N., & Ballard, D. H. (1999). Predictive coding in the visual cortex: A functional interpretation of some extra-classical receptive-field effects. *Nature Neuroscience*, *2*(1). https://doi.org/10.1038/4580

Rauss, K., & Born, J. (2017). A Role of Sleep in Forming Predictive Codes. In N. Axmacher & B. Rasch (Eds.), *Cognitive Neuroscience of Memory Consolidation* (pp. 117–132). Springer International Publishing. https://doi.org/10.1007/978-3-319-45066-7_8

Roehm, D., Sorace, A., & Bornkessel-Schlesewsky, I. (2013). Processing flexible form-to-meaning mappings: Evidence for enriched composition as opposed to indeterminacy. *Language and Cognitive Processes*, *28*(8), 1244–1274. https://doi.org/10.1080/01690965.2012.712143

Rosenblum, Y., Bovy, L., Weber, F. D., Steiger, A., Zeising, M., & Dresler, M. (2023). Increased Aperiodic Neural Activity During Sleep in Major Depressive Disorder. *Biological Psychiatry Global Open Science*, *3*(4), 1021–1029. https://doi.org/10.1016/j.bpsgos.2022.10.001

Samaha, J., & Postle, B. R. (2015). The Speed of Alpha-Band Oscillations Predicts the Temporal Resolution of Visual Perception. *Current Biology*, *25*(22), 2985–2990. https://doi.org/10.1016/j.cub.2015.10.007

Schoknecht, P., Roehm, D., Schlesewsky, M., & Bornkessel-Schlesewsky, I. (2022). The interaction of predictive processing and similarity-based retrieval interference: An ERP study. *Language, Cognition and Neuroscience*, *37*(7), 883–901. https://doi.org/10.1080/23273798.2022.2026421

Slattery, T. J., & Yates, M. (2018). Word skipping: Effects of word length, predictability, spelling and reading skill. *Quarterly Journal of Experimental Psychology*, *71*(1), 250–259. https://doi.org/10.1080/17470218.2017.1310264

Smith, N. J., & Levy, R. (2011). *Cloze but no cigar: The complex relationship between cloze, corpus, and subjective probabilities in language processing*. In Proceedings of the Annual Meeting of the Cognitive Science Society (Vol. 33, No. 33). 1637-1642. https://escholarship.org/uc/item/69s3541f

Surwillo, W. W. (1961). Frequency of the 'Alpha' Rhythm, Reaction Time and Age. *Nature*, *191*(4790). https://doi.org/10.1038/191823a0

Surwillo, W. W. (1963). The relation of simple response time to brain-wave frequency and the effects of age. *Electroencephalography and Clinical Neurophysiology*, *15*(1), 105–114. https://doi.org/10.1016/0013-4694(63)90043-9

Szewczyk, J. M., & Federmeier, K. D. (2022). Context-based facilitation of semantic access follows both logarithmic and linear functions of stimulus probability. *Journal of memory and language*, *123*, 104311. https://doi.org/10.1016/j.jml.2021.104311

Szewczyk, J. M., Mech, E. N., & Federmeier, K. D. (2020). The power of "good": Do adjectives rapidly update message level representations? Manuscript submitted for publication.

Szewczyk, J. M., & Wodniecka, Z. (2020). The mechanisms of prediction updating that impact the processing of upcoming word: An event-related potential study on sentence comprehension. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *46*(9), 1714–1734. https://doi.org/10.1037/xlm0000835

Taylor, W. L. (1953). “Cloze Procedure”: A New Tool for Measuring Readability. *Sage Journals. 30*(4). https://doi.org/10.1177/107769905303000401

Van Berkum, J. J. A., Brown, C. M., Zwitserlood, P., Kooijman, V., & Hagoort, P. (2005). Anticipating Upcoming Words in Discourse: Evidence From ERPs and Reading Times. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *31*(3), 443–467. https://doi.org/10.1037/0278-7393.31.3.443

Van Berkum, J. J. A., Hagoort, P., & Brown, C. M. (1999). Semantic Integration in Sentences and Discourse: Evidence from the N400. *Journal of Cognitive Neuroscience*, *11*(6), 657–671. https://doi.org/10.1162/089892999563724

Van Petten, C., & Luka, B. J. (2012). Prediction during language comprehension: Benefits, costs, and ERP components. *International Journal of Psychophysiology*, *83*(2), 176–190. https://doi.org/10.1016/j.ijpsycho.2011.09.015

Voytek, B., & Knight, R. T. (2015). Dynamic network communication as a unifying neural basis for cognition, development, aging, and disease. *Biological Psychiatry*, *77*(12), 1089–1097. https://doi.org/10.1016/j.biopsych.2015.04.016

Voytek, B., Kramer, M. A., Case, J., Lepage, K. Q., Tempesta, Z. R., Knight, R. T., & Gazzaley, A. (2015). Age-Related Changes in 1/f Neural Electrophysiological Noise. *Journal of Neuroscience*, *35*(38), 13257–13265. https://doi.org/10.1523/JNEUROSCI.2332-14.2015

What was new in previous releases? —MNE-BIDS 0.10 documentation. (2022). Retrieved May 20, 2022, from https://mne.tools/mne-bids/stable/whats_new_previous_releases.html

Wicha, N. Y. Y., Moreno, E. M., & Kutas, M. (2004). Anticipating Words and Their Gender: An Event-related Brain Potential Study of Semantic Integration, Gender Expectancy, and Gender Agreement in Spanish Sentence Reading. *Journal of Cognitive Neuroscience*, *16*(7), 1272–1288. https://doi.org/10.1162/0898929041920487

Wickham, H. (2016). *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York. ISBN 978-3-319-24277-4, https://ggplot2.tidyverse.org

Wolf, T., Debut, L., Sanh, V., Chaumond, J., Delangue, C., Moi, A., Cistac, P., Rault, T., Louf, R., Funtowicz, M., Davison, J., Shleifer, S., von Platen, P., Ma, C., Jernite, Y., Plu, J., Xu, C., Scao, T. L., Gugger, S., … Rush, A. M. (2020). *HuggingFace’s Transformers: State-of-the-art Natural Language Processing*. arXiv. http://arxiv.org/abs/1910.03771

Yan, S., Kuperberg, G. R., & Jaeger, T. F. (2017). Prediction (or not) during language processing. A commentary on Nieuwland et al. (2017) and DeLong et al. (2005). *BioRxiv*, 143750. https://doi.org/10.1101/143750

Appendix 1: Model comparison tables

Appendix 1 – Table 1

Akaike criterion (AIC) values for combined IAF and 1/f slope models, compared to separate IAF and 1/f slope models. P values reflect the comparison of the combined models' AIC and the IAF and 1/f slope models' AIC values, respectively.

Model number	Model outcome	Model type	AIC	*P* value
1	**Pre-article** SPP amplitude (-300 to 0ms)	Combined	136137	
		IAF	136133	0.92
		1/f slope	136136	0.16
2	**Pre-noun** SPP amplitude (-300 to 0ms)	Combined	131412	
		IAF	131409	0.75
		1/f slope	131410	0.45
3	**Post-article** N400 amplitude (200 to 500ms)	Combined	134668	
		IAF	134664	0.81
		1/f slope	134664	0.84
4	**Post-noun** N400 amplitude (200 to 500ms)	Combined	135498	
		IAF	135514	<.001
		1/f slope	135516	<.001

Appendix 1 – Table 2

Results of likelihood ratio tests comparing basic model versus complex model including random slopes.

Model number	Model type		P-value
	Basic	**Complex (with random slopes)**	
2	-65719	-65707	<.001
3	-67340	-67339	0.62
4	-67834	-67749	<.001
5	-67346	-67336	<.001
6a	-65695	-65688	<.01
6b	-65696	-65688	<.01
7	-59292	-59244	<.001

Appendix 2: Outputs of statistical models

Appendix 2 – Table 1

Model 1: SPP_amp_mean ~ cloze_scale * iaf_scale + cloze_scale * slope_scale + baseline_amp_scale + (1|subjnr) + (1|item_no), data= art_locs_sum

	SPP_amp_mean			
Predictors	*Estimates*	*std. Error*	*CI (95%)*	*p*
(Intercept)	-0.00	0.12	-0.23 – 0.23	0.993
cloze scale	0.06	0.13	-0.18 – 0.31	0.620
iaf scale	0.12	0.08	-0.04 – 0.28	0.157
slope scale	0.03	0.08	-0.13 – 0.19	0.696
baseline amp scale	-1.20	0.04	-1.27 – -1.12	**<0.001**
cloze scale × iaf scale	-0.03	0.08	-0.19 – 0.13	0.748
cloze scale × slope scale	-0.03	0.08	-0.19 – 0.13	0.715
Random Effects				
σ^2	28.78			
$\tau_{00\ subjnr}$	0.33			
$\tau_{00\ item_no}$	0.16			
ICC	0.02			
N_{subjnr}	312			
N_{item_no}	80			
Observations	21922			
Marginal R^2 / Conditional R^2	0.046 / 0.062			

Appendix 2 – Table 2

Model 2: SPP_amp_mean ~ cloze_scale * iaf_scale + cloze_scale * slope_scale + baseline_amp_scale + (1+cloze_scale|subjnr) + (1+cloze_scale|item_no), data= noun_locs_sum

	SPP_amp_mean			
Predictors	*Estimates*	*std. Error*	*CI (95%)*	*p*
(Intercept)	-1.04	0.07	-1.18 – -0.90	**<0.001**
cloze scale	0.11	0.05	0.01 – 0.21	**0.038**
iaf scale	-0.01	0.05	-0.11 – 0.10	0.882
slope scale	0.04	0.05	-0.06 – 0.14	0.449
baseline amp scale	-0.54	0.04	-0.61 – -0.46	**<0.001**
cloze scale × iaf scale	-0.05	0.04	-0.12 – 0.03	0.220
cloze scale × slope scale	-0.00	0.04	-0.08 – 0.07	0.919
Random Effects				
σ^2	27.58			
$\tau_{00\ subjnr}$	0.43			
$\tau_{00\ item_no}$	0.17			
$\tau_{11\ subjnr.cloze_scale}$	0.07			
$\tau_{11\ item_no.cloze_scale}$	0.08			
$\rho_{01\ subjnr}$	-0.20			
$\rho_{01\ item_no}$	-0.16			
ICC	0.03			
N_{subjnr}	312			
N_{item_no}	80			
Observations	21282			
Marginal R^2 / Conditional R^2	0.011 / 0.037			

Appendix 2 – Table 3

Model 3: N400_amp_mean ~ cloze_scale * iaf_scale + cloze_scale * slope_scale + prestim_scale + (1|subjnr) + (1|item_no), data= combo_art_sum

		N400_amp_mean		
Predictors	*Estimates*	*std. Error*	*CI (95%)*	*p*
(Intercept)	-0.33	0.07	-0.47 – -0.19	**<0.001**
cloze scale	-0.14	0.03	-0.20 – -0.07	**<0.001**
iaf scale	0.03	0.04	-0.06 – 0.11	0.561
slope scale	-0.00	0.04	-0.08 – 0.08	0.985
prestim scale	-1.71	0.03	-1.77 – -1.65	**<0.001**
cloze scale × iaf scale	0.00	0.03	-0.06 – 0.07	0.937
cloze scale × slope scale	-0.02	0.03	-0.09 – 0.04	0.512
Random Effects				
σ^2	21.95			
$\tau_{00\ subjnr}$	0.24			
$\tau_{00\ item_no}$	0.27			
ICC	0.02			
N_{subjnr}	312			
N_{item_no}	80			
Observations	22669			
Marginal R^2 / Conditional R^2	0.115 / 0.135			

Appendix 2 – Table 4

Model 4: N400_amp_mean ~ cloze_scale * iaf_scale + cloze_scale * slope_scale + prestim_scale + (1+cloze_scale|subjnr) + (1+cloze_scale|item_no), data= combo_noun_sum

	N400_amp_mean			
Predictors	*Estimates*	*std. Error*	*CI (95%)*	*p*
(Intercept)	1.11	0.10	0.92 – 1.31	**<0.001**
cloze scale	0.71	0.07	0.56 – 0.85	**<0.001**
iaf scale	0.15	0.07	0.01 – 0.29	**0.039**
slope scale	-0.02	0.07	-0.16 – 0.12	0.790
prestim scale	-1.97	0.03	-2.03 – -1.90	**<0.001**
cloze scale × iaf scale	-0.03	0.04	-0.11 – 0.04	0.395
cloze scale × slope scale	0.06	0.04	-0.02 – 0.13	0.127

Random Effects

σ^2	23.47
$\tau_{00\ subjnr}$	1.20
$\tau_{00\ item_no}$	0.38
$\tau_{11\ subjnr.cloze_scale}$	0.13
$\tau_{11\ item_no.cloze_scale}$	0.30
$\rho_{01\ subjnr}$	0.00
$\rho_{01\ item_no}$	0.04
ICC	0.08
N_{subjnr}	312
N_{item_no}	80
Observations	22463
Marginal R^2 / Conditional R^2	0.148 / 0.217

Appendix 2 – Table 5

Model 5: N400_amp_mean ~ art_s_scale * iaf_scale + art_s_scale * slope_scale + prestim_scale + (1+art_s_scale|subjnr) + (1+art_s_scale|item_no), data=combo_art_sum

		N400_amp_mean		
Predictors	*Estimates*	*std. Error*	*CI (95%)*	*p*
(Intercept)	-0.33	0.07	-0.47 – -0.19	**<0.001**
art s scale	-0.08	0.05	-0.18 – 0.02	0.124
iaf scale	0.02	0.04	-0.06 – 0.11	0.564
slope scale	0.00	0.04	-0.08 – 0.08	0.995
prestim scale	-1.71	0.03	-1.77 – -1.65	**<0.001**
art s scale × iaf scale	-0.02	0.04	-0.09 – 0.05	0.557
art s scale × slope scale	-0.02	0.04	-0.09 – 0.06	0.671
Random Effects				
σ^2	21.84			
$\tau_{00\ subjnr}$	0.25			
$\tau_{00\ item_no}$	0.25			
$\tau_{11\ subjnr.art_s_scale}$	0.10			
$\tau_{11\ item_no.art_s_scale}$	0.05			
$\rho_{01\ subjnr}$	-0.13			
$\rho_{01\ item_no}$	0.27			
ICC	0.03			
N_{subjnr}	312			
N_{item_no}	80			
Observations	22669			
Marginal R^2 / Conditional R^2	0.114 / 0.140			

Appendix 2 – Table 6

Model 6a: N400_amp_mean ~ art_s_scale * a1_s_scale * a2_s_scale * slope_scale + prestim_scale + (1+art_s_scale|subjnr) + (1+art_s_scale|item_no), data=combo_art_sum

	N400_amp_mean			
Predictors	*Estimates*	*std. Error*	*CI (95%)*	*p*
(Intercept)	-0.34	0.07	-0.48 – -0.20	**<0.001**
art s scale	-0.07	0.05	-0.17 – 0.03	0.177
a1 s scale	0.26	0.07	0.13 – 0.39	**<0.001**
a2 s scale	0.02	0.07	-0.11 – 0.16	0.738
slope scale	0.01	0.05	-0.08 – 0.11	0.768
prestim scale	-1.72	0.03	-1.78 – -1.66	**<0.001**
art s scale × a1 s scale	0.01	0.05	-0.08 – 0.10	0.778
art s scale × a2 s scale	-0.04	0.05	-0.13 – 0.06	0.429
a1 s scale × a2 s scale	-0.04	0.08	-0.19 – 0.11	0.600
art s scale × slope scale	0.01	0.04	-0.08 – 0.09	0.881
a1 s scale × slope scale	0.01	0.04	-0.07 – 0.08	0.856
a2 s scale × slope scale	0.00	0.04	-0.08 – 0.08	0.963
(art s scale × a1 s scale) × a2 s scale	0.11	0.05	0.01 – 0.22	**0.035**
(art s scale × a1 s scale) × slope scale	-0.06	0.04	-0.13 – 0.01	0.082
(art s scale × a2 s scale) × slope scale	-0.01	0.04	-0.08 – 0.06	0.747
(a1 s scale × a2 s scale) × slope scale	0.04	0.04	-0.05 – 0.13	0.396
(art s scale × a1 s scale × a2 s scale) × slope scale	0.05	0.04	-0.03 – 0.13	0.224

Random Effects

σ^2	21.87
$\tau_{00\ subjnr}$	0.24

$\tau_{00\ item_no}$	0.18
$\tau_{11\ subjnr.art_s_scale}$	0.10
$\tau_{11\ item_no.art_s_scale}$	0.02
$\rho_{01\ subjnr}$	-0.14
$\rho_{01\ item_no}$	0.11
ICC	0.02
N_{subjnr}	312
N_{item_no}	78
Observations	22108
Marginal R^2 / Conditional R^2	0.120 / 0.141

Appendix 2 – Table 7

Model 6b: N400_amp_mean ~ art_s_scale * a1_s_scale * a2_s_scale * iaf_scale + prestim_scale+ (1+art_s_scale|subjnr) + (1+art_s_scale|item_no), data=combo_art_sum

		N400_amp_mean		
Predictors	*Estimates*	*std. Error*	*CI (95%)*	*p*
(Intercept)	-0.34	0.07	-0.49 – -0.20	**<0.001**
art s scale	-0.07	0.05	-0.17 – 0.03	0.172
a1 s scale	0.26	0.07	0.13 – 0.39	**<0.001**
a2 s scale	0.02	0.07	-0.11 – 0.16	0.742
iaf scale	0.04	0.05	-0.06 – 0.13	0.430
prestim scale	-1.72	0.03	-1.78 – -1.66	**<0.001**
art s scale × a1 s scale	0.01	0.05	-0.08 – 0.10	0.765
art s scale × a2 s scale	-0.04	0.05	-0.13 – 0.06	0.428
a1 s scale × a2 s scale	-0.04	0.08	-0.19 – 0.11	0.592
art s scale × iaf scale	-0.04	0.04	-0.13 – 0.04	0.312
a1 s scale × iaf scale	0.04	0.04	-0.04 – 0.11	0.367
a2 s scale × iaf scale	0.03	0.04	-0.04 – 0.11	0.396
(art s scale × a1 s scale) × a2 s scale	0.11	0.05	0.01 – 0.22	**0.035**
(art s scale × a1 s scale) × iaf scale	-0.04	0.04	-0.11 – 0.03	0.292
(art s scale × a2 s scale) × iaf scale	-0.07	0.04	-0.15 – -0.00	**0.045**
(a1 s scale × a2 s scale) × iaf scale	-0.01	0.05	-0.10 – 0.08	0.839
(art s scale × a1 s scale × a2 s scale) × iaf scale	-0.04	0.04	-0.12 – 0.03	0.273

Random Effects

σ^2	21.87
$\tau_{00\ subjnr}$	0.24

$\tau_{00\ item_no}$	0.18
$\tau_{11\ subjnr.art_s_scale}$	0.10
$\tau_{11\ item_no.art_s_scale}$	0.02
$\rho_{01\ subjnr}$	-0.13
$\rho_{01\ item_no}$	0.10
ICC	0.02
N_{subjnr}	312
N_{item_no}	78
Observations	22108
Marginal R^2 / Conditional R^2	0.120 / 0.141

Appendix 2 – Table 8

Model 7: N400_amp_mean ~ noun_s_scale * iaf_scale + noun_s_scale * slope_scale + prestim_scale + (1+noun_s_scale|subjnr) + (1+noun_s_scale|item_no), data=combo_noun_sum

	N400_amp_mean			
Predictors	*Estimates*	*std. Error*	*CI (95%)*	*p*
(Intercept)	1.13	0.12	0.91 – 1.36	**<0.001**
noun s scale	-0.79	0.12	-1.03 – -0.55	**<0.001**
iaf scale	0.13	0.07	-0.01 – 0.27	0.070
slope scale	-0.04	0.07	-0.18 – 0.10	0.563
prestim scale	-1.99	0.04	-2.06 – -1.92	**<0.001**
noun s scale × iaf scale	0.03	0.04	-0.05 – 0.10	0.473
noun s scale × slope scale	-0.01	0.04	-0.08 – 0.07	0.832
Random Effects				
σ^2	23.54			
$\tau_{00\ subjnr}$	1.19			
$\tau_{00\ item_no}$	0.49			
$\tau_{11\ subjnr.noun_s_scale}$	0.06			
$\tau_{11\ item_no.noun_s_scale}$	0.71			
$\rho_{01\ subjnr}$	0.01			
$\rho_{01\ item_no}$	0.33			
ICC	0.09			
N_{subjnr}	312			
N_{item_no}	78			
Observations	19635			
Marginal R^2 / Conditional R^2	0.149 / 0.229			

Appendix 3: Outputs of SPP models with surprisal

Appendix 3 – Table 1

Model 1b: SPP_amp_mean ~ cloze_scale * iaf_scale + cloze_scale * slope_scale + a1_s_scale + baseline_amp_scale + (1|subjnr) + (1|item_no), data= art_locs_sum

	SPP_amp_mean			
Predictors	*Estimates*	*std. Error*	*CI (95%)*	*p*
(Intercept)	-0.00	0.12	-0.24 – 0.23	0.987
cloze scale	0.06	0.13	-0.19 – 0.31	0.619
iaf scale	0.12	0.08	-0.04 – 0.28	0.157
slope scale	0.03	0.08	-0.13 – 0.19	0.696
a1 s scale	0.00	0.06	-0.11 – 0.12	0.942
baseline amp scale	-1.20	0.04	-1.27 – -1.12	**<0.001**
cloze scale × iaf scale	-0.03	0.08	-0.19 – 0.13	0.748
cloze scale × slope scale	-0.03	0.08	-0.19 – 0.13	0.715
Random Effects				
σ^2	28.78			
$\tau_{00\ subjnr}$	0.33			
$\tau_{00\ item_no}$	0.16			
ICC	0.02			
N_{subjnr}	312			
N_{item_no}	80			
Observations	21922			
Marginal R^2 / Conditional R^2	0.046 / 0.062			

Appendix 3 – Table 2

Model 1a_surp: SPP_amp_mean ~ art_s_scale * iaf_scale + art_s_scale * slope_scale + baseline_amp_scale + (1|subjnr) + (1|item_no), data= art_locs_sum

		SPP_amp_mean		
Predictors	*Estimates*	*std. Error*	*CI (95%)*	*p*
(Intercept)	0.05	0.07	-0.08 – 0.18	0.494
art s scale	-0.03	0.06	-0.16 – 0.09	0.590
iaf scale	0.10	0.05	-0.00 – 0.20	0.054
slope scale	0.01	0.05	-0.09 – 0.11	0.875
baseline amp scale	-1.20	0.04	-1.27 – -1.12	**<0.001**
art s scale × iaf scale	0.03	0.04	-0.05 – 0.12	0.404
art s scale × slope scale	-0.01	0.04	-0.09 – 0.07	0.843
Random Effects				
σ^2	28.78			
$\tau_{00\ subjnr}$	0.33			
$\tau_{00\ item_no}$	0.16			
ICC	0.02			
N_{subjnr}	312			
N_{item_no}	80			
Observations	21922			
Marginal R^2 / Conditional R^2	0.046 / 0.062			

Appendix 3 – Table 3

Model 1c_slope: SPP_amp_mean ~ art_s_scale * a1_s_scale * a2_s_scale * slope_scale + baseline_amp_scale + (1+art_s_scale|subjnr) + (1|item_no), data= art_locs_sum

		SPP_amp_mean		
Predictors	*Estimates*	*std. Error*	*CI (95%)*	*p*
(Intercept)	-0.01	0.08	-0.17 – 0.15	0.897
art s scale	-0.04	0.08	-0.19 – 0.11	0.576
a1 s scale	0.00	0.07	-0.14 – 0.15	0.975
a2 s scale	-0.04	0.07	-0.18 – 0.11	0.614
slope scale	0.01	0.06	-0.10 – 0.12	0.880
baseline amp scale	-1.19	0.04	-1.26 – -1.12	**<0.001**
art s scale × a1 s scale	-0.02	0.07	-0.17 – 0.12	0.768
art s scale × a2 s scale	-0.04	0.08	-0.21 – 0.12	0.600
a1 s scale × a2 s scale	-0.17	0.09	-0.34 – 0.00	0.051
art s scale × slope scale	-0.03	0.05	-0.13 – 0.06	0.488
a1 s scale × slope scale	0.03	0.05	-0.07 – 0.12	0.580
a2 s scale × slope scale	0.01	0.05	-0.08 – 0.10	0.786
(art s scale × a1 s scale) × a2 s scale	-0.00	0.10	-0.19 – 0.18	0.963
(art s scale × a1 s scale) × slope scale	-0.04	0.05	-0.13 – 0.05	0.419
(art s scale × a2 s scale) × slope scale	-0.01	0.05	-0.11 – 0.09	0.843
(a1 s scale × a2 s scale) × slope scale	0.02	0.05	-0.08 – 0.13	0.690
(art s scale × a1 s scale × a2 s scale) × slope scale	-0.04	0.06	-0.15 – 0.08	0.544

Random Effects

σ^2	28.57
$\tau_{00\ subjnr}$	0.36

$\tau_{00\ item_no}$	0.16
$\tau_{11\ subjnr.art_s_scale}$	0.04
$\rho_{01\ subjnr}$	0.27
ICC	0.02
N_{subjnr}	312
N_{item_no}	78
Observations	21379
Marginal R^2 / Conditional R^2	0.047 / 0.065

Appendix 3 – Table 4

Model 1c_iaf: SPP_amp_mean ~ art_s_scale * a1_s_scale * a2_s_scale * slope_scale + baseline_amp_scale + (1+art_s_scale|subjnr) + (1|item_no), data= art_locs_sum

	SPP_amp_mean			
Predictors	*Estimates*	*std. Error*	*CI (95%)*	*p*
(Intercept)	-0.01	0.08	-0.17 – 0.14	0.871
art s scale	-0.04	0.08	-0.19 – 0.11	0.590
a1 s scale	-0.00	0.07	-0.15 – 0.14	0.996
a2 s scale	-0.04	0.07	-0.18 – 0.11	0.603
iaf scale	0.14	0.06	0.03 – 0.25	**0.014**
baseline amp scale	-1.19	0.04	-1.26 – -1.12	**<0.001**
art s scale × a1 s scale	-0.02	0.07	-0.16 – 0.13	0.799
art s scale × a2 s scale	-0.04	0.08	-0.21 – 0.12	0.623
a1 s scale × a2 s scale	-0.17	0.09	-0.34 – -0.00	**0.048**
art s scale × iaf scale	0.03	0.05	-0.07 – 0.12	0.585
a1 s scale × iaf scale	0.10	0.05	0.01 – 0.19	**0.031**
a2 s scale × iaf scale	0.01	0.05	-0.09 – 0.10	0.891
(art s scale × a1 s scale) × a2 s scale	-0.00	0.10	-0.19 – 0.19	0.988
(art s scale × a1 s scale) × iaf scale	-0.07	0.05	-0.17 – 0.02	0.118
(art s scale × a2 s scale) × iaf scale	-0.08	0.05	-0.18 – 0.03	0.152
(a1 s scale × a2 s scale) × iaf scale	0.06	0.05	-0.05 – 0.17	0.269
(art s scale × a1 s scale × a2 s scale) × iaf scale	0.03	0.06	-0.08 – 0.15	0.571

Random Effects

σ^2	28.56
$\tau_{00\ subjnr}$	0.35
$\tau_{00\ item_no}$	0.16

$\tau_{11\ subjnr.art_s_scale}$	0.04
$\rho_{01\ subjnr}$	0.24
ICC	0.02
N_{subjnr}	312
N_{item_no}	78
Observations	21379
Marginal R^2 / Conditional R^2	0.047 / 0.065

Appendix 3 – Table 5

Model 2b: SPP_amp_mean ~ cloze_scale * iaf_scale + cloze_scale * slope_scale + baseline_amp_scale + art_s_scale + (1|subjnr) + (1+cloze_scale|item_no), data= noun_locs_sum

		SPP_amp_mean		
Predictors	*Estimates*	*std. Error*	*CI (95%)*	*p*
(Intercept)	-1.04	0.07	-1.18 – -0.90	**<0.001**
cloze scale	0.11	0.05	0.01 – 0.20	**0.030**
iaf scale	-0.01	0.05	-0.11 – 0.10	0.872
slope scale	0.04	0.05	-0.06 – 0.14	0.450
baseline amp scale	-0.54	0.04	-0.61 – -0.46	**<0.001**
art s scale	0.03	0.05	-0.07 – 0.14	0.558
cloze scale × iaf scale	-0.05	0.04	-0.12 – 0.02	0.199
cloze scale × slope scale	-0.00	0.04	-0.07 – 0.07	0.974
Random Effects				
σ^2	27.66			
$\tau_{00\ subjnr}$	0.43			
$\tau_{00\ item_no}$	0.17			
$\tau_{11\ item_no.cloze_scale}$	0.08			
$\rho_{01\ item_no}$	-0.18			
ICC	0.02			
N_{subjnr}	312			
N_{item_no}	80			
Observations	21282			
Marginal R^2 / Conditional R^2	0.011 / 0.035			

Appendix 3 – Table 6

Model 2a_surp: SPP_amp_mean ~ noun_s_scale * iaf_scale + noun_s_scale * slope_scale + baseline_amp_scale + (1|subjnr) + (1+noun_s_scale|item_no), data= noun_locs_sum

	SPP_amp_mean			
Predictors	*Estimates*	*std. Error*	*CI (95%)*	*p*
(Intercept)	-0.98	0.07	-1.13 – -0.84	**<0.001**
noun s scale	-0.16	0.06	-0.28 – -0.04	**0.009**
iaf scale	-0.00	0.05	-0.11 – 0.10	0.956
slope scale	0.07	0.05	-0.03 – 0.18	0.174
baseline amp scale	-0.54	0.04	-0.61 – -0.46	**<0.001**
noun s scale × iaf scale	-0.01	0.04	-0.08 – 0.07	0.891
noun s scale × slope scale	0.05	0.04	-0.03 – 0.13	0.220
Random Effects				
σ^2	27.61			
$\tau_{00\ subjnr}$	0.42			
$\tau_{00\ item_no}$	0.17			
$\tau_{11\ item_no.noun_s_scale}$	0.07			
$\rho_{01\ item_no}$	0.09			
ICC	0.02			
N_{subjnr}	312			
N_{item_no}	78			
Observations	18622			
Marginal R^2 / Conditional R^2	0.011 / 0.034			

Appendix 3 – Table 7

Model 2c_slope: SPP_amp_mean ~ noun_s_scale * art_s_scale * a1_s_scale * slope_scale + baseline_amp_scale + (1|subjnr) + (1+noun_s_scale|item_no), data= noun_locs_sum

	SPP_amp_mean			
Predictors	*Estimates*	*std. Error*	*CI (95%)*	*p*
(Intercept)	-1.01	0.07	-1.15 – -0.87	**<0.001**
noun s scale	-0.18	0.06	-0.30 – -0.05	**0.005**
art s scale	0.00	0.06	-0.11 – 0.11	0.996
a1 s scale	0.08	0.07	-0.06 – 0.21	0.262
slope scale	0.07	0.05	-0.03 – 0.18	0.181
baseline amp scale	-0.53	0.04	-0.61 – -0.46	**<0.001**
noun s scale × art s scale	-0.08	0.07	-0.21 – 0.05	0.229
noun s scale × a1 s scale	-0.06	0.07	-0.19 – 0.08	0.414
art s scale × a1 s scale	0.10	0.06	-0.01 – 0.21	0.063
noun s scale × slope scale	0.04	0.04	-0.04 – 0.12	0.350
art s scale × slope scale	-0.02	0.04	-0.10 – 0.06	0.697
a1 s scale × slope scale	0.05	0.04	-0.04 – 0.13	0.253
(noun s scale × art s scale) × a1 s scale	-0.04	0.07	-0.18 – 0.11	0.598
(noun s scale × art s scale) × slope scale	-0.01	0.04	-0.10 – 0.07	0.803
(noun s scale × a1 s scale) × slope scale	-0.05	0.05	-0.14 – 0.03	0.231
(art s scale × a1 s scale) × slope scale	-0.01	0.04	-0.10 – 0.07	0.727
(noun s scale × art s scale × a1 s scale) × slope scale	0.03	0.05	-0.07 – 0.13	0.505

Random Effects

σ^2	27.62
$\tau_{00\ subjnr}$	0.41
$\tau_{00\ item_no}$	0.15
$\tau_{11\ item_no.noun_s_scale}$	0.08
$\rho_{01\ item_no}$	0.17
ICC	0.02
N_{subjnr}	312
N_{item_no}	78
Observations	18622
Marginal R^2 / Conditional R^2	0.012 / 0.035

Appendix 3 – Table 8

Model 2c_iaf: SPP_amp_mean ~ noun_s_scale * art_s_scale * a1_s_scale * iaf_scale + baseline_amp_scale + (1|subjnr) + (1+noun_s_scale|item_no), data= noun_locs_sum

	SPP_amp_mean			
Predictors	*Estimates*	*std. Error*	*CI (95%)*	*p*
(Intercept)	-1.01	0.07	-1.16 – -0.87	**<0.001**
noun s scale	-0.18	0.06	-0.30 – -0.05	**0.005**
art s scale	0.00	0.06	-0.11 – 0.11	0.976
a1 s scale	0.08	0.07	-0.06 – 0.21	0.270
iaf scale	-0.01	0.05	-0.12 – 0.09	0.799
baseline amp scale	-0.54	0.04	-0.61 – -0.46	**<0.001**
noun s scale × art s scale	-0.08	0.07	-0.21 – 0.05	0.229
noun s scale × a1 s scale	-0.06	0.07	-0.19 – 0.08	0.418
art s scale × a1 s scale	0.10	0.06	-0.01 – 0.21	0.063
noun s scale × iaf scale	0.00	0.04	-0.08 – 0.08	0.981
art s scale × iaf scale	-0.01	0.04	-0.09 – 0.08	0.880
a1 s scale × iaf scale	-0.05	0.04	-0.13 – 0.04	0.294
(noun s scale × art s scale) × a1 s scale	-0.04	0.07	-0.19 – 0.11	0.596
(noun s scale × art s scale) × iaf scale	0.04	0.04	-0.05 – 0.13	0.362
(noun s scale × a1 s scale) × iaf scale	0.06	0.05	-0.03 – 0.15	0.209
(art s scale × a1 s scale) × iaf scale	0.02	0.04	-0.06 – 0.10	0.603
(noun s scale × art s scale × a1 s scale) × iaf scale	-0.04	0.05	-0.14 – 0.06	0.467

Random Effects

σ^2	27.62
$\tau_{00\ subjnr}$	0.42

$\tau_{00\ item_no}$	0.15
$\tau_{11\ item_no.noun_s_scale}$	0.08
$\rho_{01\ item_no}$	0.16
ICC	0.02
N_{subjnr}	312
N_{item_no}	78
Observations	18622
Marginal R^2 / Conditional R^2	0.012 / 0.035