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Conditionals in context: Brain signatures of prediction in discourse processing

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ABSTRACT

Comprehenders are known to generate expectations about upcoming linguistic input at the sentence and discourse level. However, most previous studies on prediction focused mainly on word-induced brain activity rather than examining neural activity preceding a critical stimulus in discourse processing, where prediction actually takes place. In this EEG study, participants were presented with multiple sentences resembling a discourse including conditional sentences with either *only if* or *if*, which are characterized by different semantics, triggering stronger or weaker predictions about the possible continuation of the presented discourses, respectively. Results revealed that discourses including *only if*, as compared to discourses with bare *if*, triggered an increased predictive neural activity before the expected critical word, resembling the readiness potential. Moreover, word-induced P300 brain responses were found to be enhanced by unpredictable discourse continuations and reduced in predictable discourse continuations. Intriguingly, brain responses preceding and following the critical word were found to be correlated, which yields evidence for predictive activity modulating word-induced processing on the discourse level. These findings shed light on the predictive nature of neural processes at the discourse level, critically advancing our understanding of the functional interconnection between discourse understanding and prediction processes in brain and mind.

1. Introduction

In everyday social interaction, conversational partners frequently adjust their expectations about the forthcoming actions and linguistic input (Federmeier, 2007; Heilbron, Armeni, Schoffelen, Hagoort, & de Lange, 2020; Huettig & Janse, 2016; Pickering & Garrod, 2013; Van Petten & Luka, 2012; Willems, Frank, Nijhof, Hagoort, & van den Bosch, 2016). Prediction mechanisms have been shown to facilitate language processing at different levels of linguistic representations, including phonological (e.g. DeLong, Urbach, & Kutas, 2005; Nicenboim, Vasishth, & Rösler, 2020), morpho-syntactic (e.g. Lau, Stroud, Plesch, & Phillips, 2006; Szewczyk & Schriefers, 2013; Wicha, Moreno, & Kutas, 2004), semantic (Altmann & Kamide, 1999; Federmeier & Kutas, 1999; Weber, Lau, Stillerman, & Kuperberg, 2016), as well as discourse level processing (Nieuwland & Van Berkum, 2006; Otten & Van Berkum, 2008; Rohde & Horton, 2014; Rohde, Levy, & Kehler, 2011; Scholman, Rohde, & Demberg, 2017; Schwab & Liu, 2020; Xiang & Kuperberg, 2015). A range of electrophysiological experiments have explored neural markers underlying predictive processes during the comprehension of sentences with words of varying predictability. A well-known event-related brain potential (ERP) component that is strongly modulated by prediction is the N400, a negative-going response that peaks about 400 milliseconds after the target word onset. For example, in a sentence like "I want an ice cream with *bacon*", the unpredictable word *bacon* would elicit a stronger N400 response as compared to a more predictable word such as *chocolate*. Thus, the N400 effect has been interpreted as an index of semantic violation or prediction error (e.g. Rabovsky, Hansen, & McClelland, 2018; see Kutas & Federmeier, 2011, for a review). Beyond the sentence level, Xiang and Kuperberg (2015), for example, show that the discourse connective *even so* reverses comprehenders' expectations

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about the forthcoming sentence, so that unlikely events (e.g. "I failed my history exam. (Even so), I went home and celebrated wildly.") become more expected, leading to an attenuated N400 after coherent versus incoherent target words (e.g. *celebrated*). Furthermore, more vs. less predictable input has also been related to a positive going response that peaks about 300 milliseconds after word onset, the so-called P300 component, in oddball paradigms (see Picton, 1992 for a review) as well as in memory updating or revision of the mental representation of the upcoming stimulus (context updating) (see Polich, 2007 for a review). Such an effect was particularly observed when the (un)expected target word played a crucial role in performing a categorization task with a binary choice (Alday & Kretzschmar, 2019). Thus, the N400 and P300 components in the time window between 250 and 500 ms appear to be crucial word-induced brain indicators of contextual predictability and information processing after word onset. Nevertheless, the relationship between P300 and N400 as well as their specific relations to cognitive processes are far from clear (Alday & Kretzschmar, 2019; Arbel, Spencer, & Donchin, 2011; Kutas & Hillyard, 1980). These general questions, although relevant, are beyond the scope of the current paper.

While brain responses in reaction to linguistic stimuli seem to be modulated by predictability, they have been argued to be only an indirect measure of prediction and possibly reflect processes of lexical access or integration during language comprehension (Baggio & Hagoort, 2011; Pickering & Gambi, 2018). Recently, a few experimental studies have addressed this problem and discovered a more direct neurophysiological measure of prediction that occurs prior to the upcoming predictive information: the so-called Prediction Potential, a slowly building negative electroencephalographic signature resembling the readiness potential that increases right *before* the target word (Grisoni, Miller, & Pulvermüller, 2017; Grisoni, Tomasello, & Pulvermüller, 2021; León-Cabrera, Flores, Rodríguez-Fornells, & Morís, 2019; León-Cabrera, Rodríguez-Fornells, & Morís, 2017). For example, Grisoni et al. (2021) documented anticipatory brain activity for words that were highly predictable from previous sentence fragments (e.g., "The emblem of Germany is the *eagle.*"), whereas it was absent when the sentence-initial fragment was not a strong predictor of the sentence-final word (e.g., "The emblem of my family is the *eagle.*"). Less predictable sentence endings led to a larger N400 than more predictable ones and, importantly, the amplitudes of the Prediction Potential and the N400 were inversely correlated, with higher Prediction Potentials leading to attenuated N400 responses. This suggests that N400 responses are related to brain activity prior to the presentation of the predicted information in a sentence. Although these recent results shed light on novel brain correlates of prediction, most work has examined prediction and related comprehension processes at the level of sentences presented in isolation. Less work has looked at the neurobiology of prediction spanning multiple sentences, where various semantic and pragmatic processing steps are at work to accurately predict the possible continuation of an ongoing discourse.

To investigate predictive processes in discourse comprehension, we used conditional sentences of the form '*If the flowers are beautiful, he'll pick them.*', which express the dependency relation between the condition or antecedent proposition *P* (the flowers being beautiful) and the consequent *Q* (he picking them). Their comprehension involves semantic as well as contextual-pragmatic integration. Central to the present study, depending on the contextual situation and on which kind of conditional is used, more or less precise predictions can be generated. For instance, conditionals with *only if* like '*Only if the flowers are beautiful, he'll pick them*', entail that the falsity of the antecedent, i.e., *not-P* (the flowers not being beautiful), is a sufficient condition for the falsity of the consequent, i.e., *not-Q* (him not picking them) (Barthel, Tomasello, & Liu, 2022; Herburger, 2015, 2019; Liu & Barthel, 2021). In contrast, bare *if* conditionals like '*If the flowers are beautiful, he'll pick them*' do not carry such an entailment, that is, in the same context of *not-P* ('*the flowers are not beautiful*'), it is unclear whether *Q* will follow or not ('*he'll pick them*' vs. '*he won't pick them*'). Hence, if the antecedent is known to be false ('*the flowers are not beautiful*'), as in the critical materials of this study, *only if* conditionals give rise to a strong expectation of a false consequent to follow ('*he won't pick them*'), creating a predictable scenario. In bare *if* conditionals, on the other hand, the truth or falsity of the consequent is not strongly predictable, with a binary possible continuation of speaker actions (picking the flowers or not), which creates a less predictable scenario.

Following these reflections, in our previous study (Barthel et al., 2022), we presented short stories in German containing *if* vs. *only if* conditional sentences, followed by a sentence that negated the antecedent of the conditional ('*If P, Q. Not P.*'), as described above. In a final sentence, the consequent of the conditional was presented as being either true or false ('*Q.*' / '*Not Q.*'). Reading times of the critical words in negated consequents (i.e., the negative quantifier *none* in '*Not Q.*') were found to be shorter after *only if* conditionals than after bare *if* conditionals. This finding supports previous analyses of the meaning differences between *if* and *only if* conditionals and provides first evidence for repercussions of these differences on the online processing of discourse continuations after conditionals. Specifically, the observed difference in reading times was attributed to a stronger prediction about the discourse continuation triggered by contexts in which *only if* conditionals were used, as compared to contexts in which bare *if* conditionals were used. Yet, these behavioral data are only indirect measures of the underlying neural processes involved in discourse prediction. Thus, a neurophysiological approach using electroencephalographic recordings (EEG) is needed, allowing for direct monitoring of predictive brain processes with high time resolution.

Previous studies already shed light on the brain correlates of expectation in discourse continuation across multiple sentences guided by discourse markers, referential expressions, or logical connectives (Bonnefond et al., 2012; Bonnefond & Van der Henst, 2009; Brilmayer & Schumacher, 2021; Carter & Nieuwland, 2022; Drenhaus, Demberg, Köhne, & Delogu, 2014; Nieuwland & Van Berkum, 2006; Rasenberg, Rommers, & van Bergen, 2020; Scholman et al., 2017; Van Berkum, Brown, Zwitserlood, Kooijman, & Hagoort, 2005). However, these studies focused on the effects of prediction on the site of what was (or was not) predicted, that is, they investigated effects occurring *after* the predicted information had been presented or they investigated differences in the time frequency domain in brain activity related to prediction (e.g., Gisladottir, Bögels, & Levinson, 2018; León-Cabrera, Piai, Morís, & Rodríguez-Fornells, 2022; Lewis, Wang, & Bastiaansen, 2015; Rommers, Dickson, Norton, Wlotko, & Federmeier, 2017; Terporten, Schoffelen, Dai, Hagoort, & Kösem, 2019; Wang, Zhu, & Bastiaansen, 2012). Although there has been extensive discussion on brain preactivation related to prediction before the expected word (e.g., Federmeier, 2007; Szewczyk & Schriefers, 2013; Van Berkum et al., 2005), less work has been conducted at the level of ERPs appearing before the predicted critical words (i.e., Prediction Potential).

To close this gap, we measure predictive brain activity in scenarios with *if* vs. *only if* conditionals, contrasting more or less predictable discourses containing everyday courses of action spanning multiple sentences, while keeping syntactic, semantic, and lexical contexts maximally equal across conditions. Building on our previous results (Barthel et al., 2022) that revealed differences in reading times between scenarios containing these conditionals, we present discourses containing a conditional (*If / Only if P, Q.*) followed by a sentence negating the antecedent of the conditional (*Not P.*; see Section 2.2 for an example). In these scenarios, discourses containing *only if* conditionals are expected to be more predictable regarding the scenario continuation than bare *if* conditionals, with '*Not Q*' being a highly predictable continuation in *only if* scenarios but not in bare *if* scenarios. Consequently, we expect larger anticipatory neural activity, the Prediction Potential, before the scenario conclusion in *only if* scenarios than in bare *if* scenarios. Furthermore, in *only if* scenarios, as compared to in bare *if* scenarios, we expect attenuated word-induced brain responses in the N400/P300 time window after the negative critical word in the negated consequents (*Not Q.*). It is worth noting that P300 effects have also been found in response to surprising physical properties of visually presented words (Arbel et al., 2011; Kutas & Hillyard, 1980). However, in the present design, if such P300 effects were to emerge, it could not be related to differences in the presented verbal material, as we compared ERP responses to identical word forms (the quantifiers *one* and *none*) across the different conditional scenarios that were embedded within the same discourses. Finally, discourse processing can be hypothesized to be easier with expected discourse continuations than with unexpected continuations (Schumacher, 2014; Xiang & Kuperberg, 2015; Zwaan & Radvansky, 1998). Thus, if predictive activity preceding the predicted discourse ending has an influence on word-induced discourse processing, we should observe a correlation of ERP activation before the critical word (indicating prediction) and word-induced ERP activation (indicating input processing and integration).

2. Methods

2.1. Participants

Thirty-eight healthy right handed volunteers (mean age in years = 25.5 (SD = 4.8), min: 20; max: 35) took part in the study. All subjects were German native speakers with normal or corrected to normal vision who had no neurological or psychiatric condition and were paid for their participation. All subjects were right-handed, as assessed with the Edinburgh Handedness Inventory test (Oldfield, 1971; mean laterality quotient (SD) = +80.7 (21.3)). One participant's data had to be discarded due to technical failure during recording and another participant's data was not analyzed as they were not following or understanding the task instructions. Ethics approval was obtained from the ethics committee of Osnabrück University. All participants gave their informed consent prior to the experiment.

2.2. Materials and design

192 short stories consisting of four German sentences (S1-S4) were constructed, partly taken from a previous self-paced reading study (Barthel et al., 2022). 144 stories served as critical items and 48 as filler items. All story items were constructed in four conditions, with a 2 × 2 study design with Conditional Connective (if / only if) and Quantifier (positive / negative) as factors.

The critical items were constructed as follows: S1 introduced the situational context in either six or seven words, always using the structure "proper name + VP + '*and thought:*'". S2 contained a conditional of the form '*If / Only if P, Q.*' with either the conditional connective '*Wenn*' (if) or '*Nur wenn*' (only if), expressing a possible future action in the consequent (*Q*) and its condition in the antecedent (*P*). S3 negated the antecedent of the conditional (*Not P.*). S4 revealed the story conclusion, with the consequent of the conditional either being confirmed and the action executed (*Q*), or negated and the action not executed (*Not Q*). Whether the action was executed or not was always revealed by a quantifier referencing the object of the conditional. A positive quantifier ('*ein*' / '*eine*' / '*einen*' (one)) in S4 confirmed the consequent (*Q*), while a negative quantifier ('*kein*' / '*keine*' / '*keinen*' (none)) negated the consequent (*Not Q*). Sentences in S2 to S4 always used the same structure and were always of the same length, namely nine to ten words for S2, depending on the conditional connective used, eight words for S3, and nine words for S4. Note that the presented discourses were exactly the same between conditions and only differed in the respective conditional connectives (*if* vs. *only if*) and quantifiers (*one* vs. *none*) used. See an example of a critical item below.

Example:

S1. *Leon besuchte seine Eltern und dachte sich:* (Leon visited his parents and thought:)

S2. ***Wenn / Nur wenn*** *die Blumensträuße hübsch sind, nehme ich einen mit.* (**If / Only if** the bouquets are pretty, I will take one with me.)

S3. *Wie sich zeigte, waren die Blumensträuße nicht hübsch.* (As became apparent, the bouquets were not pretty.)

S4. *Von denen brachte er* ***einen / keinen*** *mit und ging weiter.* (Of those he took **one / none** with him and went on.)

In summary, the different types of conditionals (*if / only if*) in S2 allowed for stronger or weaker predictions about the continuation of the discourse in S4. The quantifiers (one / none) in S4 revealed the continuation of the discourse and served as the critical words for our measures of predictive and word-induced brain activity.

As for the filler items, the story and sentence structures were identical to critical scenarios, except that in fillers S3 confirmed the antecedent of the conditional (*P*; e.g. '*Wie sich zeigte, waren die Blumensträuße hübsch.*' (As became apparent, the bouquets were pretty.)). Fillers were included to increase variation and thus keep participants' attention to the stories continuously high throughout the experiment. Brain responses to fillers were not analyzed.

Four counterbalanced experimental lists were produced, with each item appearing only once per list and in different conditions across lists. Each subject was tested in only one of the lists, and thus presented with 36 trials in each of the four critical conditions plus 48 filler trials.

2.3. Procedure

Items were presented with Presentation (v. 23; Neurobehavioral Systems) on a 21-in. screen with a 1024 × 768 pixels resolution. Subjects were seated approximately 80 cm away from the screen and instructed to attentively and silently read the presented stories without any vocalization. A trial started with a fixation cross at the center of the screen for 500 ms. Subsequently, S1 to S3 were presented visually as complete sentences in the center of the screen for 1600 ms each, with an interstimulus interval of 600 ms showing a black screen. S4 was presented visually word by word in the center of the screen for 150 ms each, with an interstimulus interval of 500 ms (varying randomly by ±10 ms) showing a black screen. Right before the critical word (the positive or negative quantifier), a black screen was presented for 1000 ms. The longer break, which was equally present in all conditions, was necessary to separate the neurophysiological responses of the previous sentence segment from the critical words, thus allowing for an improved signal to noise ratio (see e.g., Grisoni et al., 2021; León-Cabrera et al., 2019).

The 192 trials were divided into 4 counterbalanced blocks of 48 trials each. Trials in each block were presented in random order. Each block lasted about twelve minutes and was followed by a short break. The experiment was preceded by twelve practice trials that were not analyzed. In order to assess whether subjects were reading the scenarios attentively during the main experiment, participants ran a surprise memory test after the EEG recording in which they were asked to categorize 64 scenarios into read / not read (32 scenarios were actually contained in the experiment, 32 were not contained; e.g. "*Did someone visit their parents?*") by pressing one of two buttons on a response box using their index fingers.

2.4. EEG data recording and pre-processing

The EEG was recorded via 32 active electrodes (Brain Products GmbH, Munich, Germany). 26 electrodes were embedded in a cloth cap, distributed across the scalp, and 6 electrodes were assigned as EOG electrodes, 4 placed above and below the left and right eyes and 2 to the left and right outer canthus to measure the vertical and horizontal electro-oculograms. All electrodes were referenced to an electrode placed on the tip of the nose. Data were amplified and recorded using the Brain Vision Recorder (version 1.20.0601; Brain Products GmbH), with a passband of 0.01–500 Hz, sampled at 1000 Hz and stored on disk. Impedances of all active electrodes were kept below 10 KΩ.

The following offline pre-processing analyses were carried out with EEGLAB 2021.1 (Delorme & Makeig, 2004). Raw, unsegmented EEG data were down-sampled to 500 Hz and high-pass filtered at 0.1 Hz along with a notch filter around 50 Hz using the finite impulse response (FIR) filter. To obtain the vertical EOG, the difference between the upper and lower left eye electrodes were calculated, and the horizontal EOG was computed from the average of the latter two minus the potential at the right outer canthus. Afterwards, independent component analysis (ICA) with the algorithm *runica* (Bell & Sejnowski, 1995) was used to derive 26 components from the data. Components that correlated with either vEOG or hEOG with $r < -0.3$ or $r > 0.3$ were removed from the data, reducing eye-related artefacts (see Groppe, Makeig, & Kutas, 2009; Hanna, Kim, & Müller-Voggel, 2020; Tomasello, Grisoni, Boux, Sammler, & Pulvermüller, 2022, for previous work applying this method). On average, 4.38 (SD = 1.77) components were removed from each subject dataset after ICA.

The data were then epoched into smaller segments for the predictive response (i.e., the Prediction Potential analysis), starting 700 ms before critical word onset and ending at critical word onset. As a slow wave potential, the so-called Prediction Potential, appeared at about 500 ms before word onset, we used the time window from −700 ms to −600 ms as a baseline period, following the same procedure described in previous studies investigating the Prediction Potential component (Boux, Tomasello, Grisoni, & Pulvermüller, 2021; Grisoni et al., 2021; Kilner, Vargas, Duval, Blakemore, & Sirigu, 2004; León-Cabrera et al., 2019). Epochs with signals exceeding −100 and 100 μV were discarded, leading to the rejection of two data sets (i.e., subjects) with <50% of remaining trials. Two more subjects were removed due to technical reasons or due to misunderstanding the task of the experiment, respectively. Hence, data from 34 subjects entered the final EEG analysis. In this sample, the average trial rejection rate was 6.9%, with very similar sample sizes remaining across conditions (only if / negative: $M = 31.9$, $SD = 3.98$; only if / positive: $M = 30.7$, $SD = 5.04$; if / negative: $M = 31.6$, $SD = 5.26$; if / positive: $M = 31.4$, $SD = 4.13$; a two-way ANOVA showed that rejection rates did not differ between conditions (all $ps > 0.4$)). The same pre-processing procedure was carried out on the word-induced brain response analysis, starting 100 ms before critical word onset and ending 650 ms after critical word onset. For baseline correction, the 100 ms pre-stimulus interval before critical word onset (−100 ms to 0 ms) was used. We applied such a baseline to obtain directly comparable results to previous neurophysiological studies that commonly adopted this procedure to investigate post-stimulus brain responses (e.g., Federmeier, Wlotko, De Ochoa-Dewald, & Kutas, 2007). Data from the same 34 subjects entered the final EEG analysis, with an average trial rejection rate of 8.9%, again with very similar sample sizes remaining across conditions (only if / negative: $M = 32.9$, $SD = 3.22$; only if / positive: $M = 32.4$, $SD = 3.73$; if / negative: $M = 32.8$, $SD = 4.27$; if / positive: $M = 32.3$, $SD = 3.62$; a two-way ANOVA showed that rejection rates did not differ between conditions (all $ps > 0.4$)). 92.8% of the set of trials analyzed for predictive brain activity before word onset were present in the set of trials analyzed in the word-induced analysis, making the data sets suitable for further analyses.

2.5. ERP analysis

2.5.1. Predictive brain activation

Previous work reported predictive brain activity, the so-called Prediction Potential, appearing before the onset of the expected word (Grisoni et al., 2017, 2021; León-Cabrera et al., 2019). To examine if this brain indicator appears prior to the expected discourse continuation (i.e., the critical quantifier *one / none*) and whether it is modulated by the different types of conditionals (*if* vs *only if*), we applied two-tailed (non-parametric) Monte Carlo Cluster Based Permutation Tests as implemented in FieldTrip toolbox for MATLAB (Oostenveld, Fries, Maris, & Schoffelen, 2011). Specifically, the statistical analyses were run on two time windows from −300 ms to −150 ms and from −150 ms to 0 (i.e., quantifier onset) on 24 fronto-central-parietal-occipital electrodes (F3, FC5, P7, PO9, FC1, C3, P3, O1, FP1, FP2, Fz, Cz, CP1, CP2, Pz, Oz, F4, FC2, FC6, C4, P4, P8, O2, PO10). The time window of −150 ms to 0 ms was motivated by previous studies showing that the predictive brain activity has the greatest amplitude and highest signal-to-noise ratio right before word onset (Grisoni et al., 2017; León-Cabrera et al., 2019). The time window of (−300 ms to −150 ms) was included to test if any effect of prediction appeared even before word onset. Note however, that all the main analyses in the present study were run on the first time window (−150 ms to 0 ms), in accordance with previous studies mentioned above. Since predictive neural markers are expected to be stronger in *only if* trials than in *if* trials, a one-tailed test was applied to test for significant clusters. Cluster-based permutation tests were calculated by randomly interchanging the data between the two stimulus conditions for 10.000 permutations and finding the maximum positive and negative clusters of each permutation. The cluster based permutation test was complemented with a linear mixed-effects regression model (LMM) built with *lme4* (Bates, Mächler, Bolker, & Walker, 2015) in *R* (v. 4.1.3; R Core Team, 2021), modeling average brain potentials of single trials within a time window spanning the 150 ms immediately before the onset of the critical quantifier (−150 ms to 0 ms). For a more fine-grained examination of the effects in the LMM, the 24 electrodes were coded for their scalp location into 6 regions of interest (ROIs) defined by two factors of location: Laterality (3 levels: left (F3, FC5, P7, PO9, FC1, C3, P3, O1), middline (Fp1, Fp2, Fz, Cz, CP1, CP2, Pz, Oz), right (F4, FC2, FC6, C4, P4, P8, O2, PO10)); and Antpost (2 levels): anterior (Fp1, Fp2, F3, F4, Fz, FC1, FC2, FC5, FC6, C3, C4, Cz), posterior (CP1, CP2, P3, P4, P7, P8, Pz, O1, O2, PO9, PO10, Oz)). All models contained the maximal fixed-effects structure, with the deviation coded factors Connective (*if / only if*), Laterality (left, midline, right), and Antpost (anterior and posterior) as well as all their interactions as predictors. Both by-subject and by-item random intercepts were modeled to vary. Additionally, random slopes of Connective were modeled to vary by subject, with freely varying correlations, accounting for inter-subject variability. Type III anova tests of significance were conducted with Kenward-Roger approximations of degrees of freedom using the *R* package *car* (Fox & Weisberg, 2019; Halekoh & Hojsgaard, 2014; Kenward & Roger, 1997). Post-hoc tests for significance of simple effects causing significant interactions were based on *F*-tests comparing estimated marginal means of factor levels (Searle, Speed, & Milliken, 1980) that were conducted using the *R* package *emmeans* (v. 1.8.0; Lenth, 2019) and corrected for multiple comparisons by using the multivariate *t*-distribution with the same covariance structure as the estimates to determine applicable adjustments.

2.5.2. Word-induced brain activation

To investigate word-induced brain responses of the critical quantifiers, two two-tailed cluster-based permutation tests parallel to those described above for the analyses of predictive brain activation were performed across the 24 electrodes described above. In these cluster-based permutation tests, word-induced brain responses to positive and negative quantifiers were analyzed separately, comparing responses from 200 ms to 600 ms after critical word onset in *if* vs. *only if* scenarios. The time window was chosen based on previous ERP studies showing that unexpected words trigger stronger brain activation than expected words (e.g. Bornkessel-Schlesewsky et al., 2015; Federmeier, 2007; Grisoni et al., 2017; Kutas & Federmeier, 2011). To investigate the timing and location of peaks of brain responses in more detail and at the level of single trials, the cluster based permutation tests were complemented with Linear mixed Models (LMMs) modeling average brain potentials in two more narrow time windows. To define the time windows for these analyses, the Root Mean Square (RMS) of all pooled trials in all conditions was computed across all scalp electrodes and all subjects. Time windows were chosen based on visual observation of the peaks and amplitudes of the RMS. The same topographical factors Laterality (3 levels) and Antpost (2 levels) that were used in the analysis of anticipatory brain activation before word onset were included. Model structures were also parallel to the analyses on the data from the predictive brain activity, but with Quantifier (positive / negative) as an additional factor, including interactions with all other factors. As in the predictive analysis, both by-subject and by-item random intercepts were modeled to vary. Additionally, random slopes of both Connective and Quantifier were modeled to vary by subject, with freely varying correlations, accounting for inter-subject variability. Tests of significance were conducted as in the analysis of predictive brain activation.

2.5.3. Correlation analysis

To test for a functional link between brain signatures before and after critical word onset, Pearson correlation tests were conducted using the *stats* package in *R* on single trials. Specifically, for *only if* trials (where we expect subjects to predict the upcoming quantifier revealing the discourse continuation), Pearson correlations of the mean Prediction Potentials (i.e., from −150 ms to 0 ms before critical word onset) and the mean word-induced potentials (from 220 ms to 480 ms past critical word onset) were computed. Correlations were computed separately for positive and negative quantifiers. Driven by the obtained data, we ran the correlation tests on a subset of electrodes that showed both the Prediction Potential activity as well as the word-induced activities (FC5, FC6, C3, C4, CP1, CP2, P3, P4, O1, O2, see Section 3.2). To statistically compare correlation coefficients obtained for the different quantifiers, *Z*-Fisher transformations have been used, computing z-scores for each condition from the respective correlation coefficients and the conditions' sample sizes and comparing these *z*-scores, yielding a *p*-value for the probability of the compared correlations being statistically equal.

To make sure that the correlation analysis described above is not affected by the word-induced baseline correction before word onset, where much anticipatory activity is found, we ran another correlation analysis as described above, this time between the Prediction Potential and a very early P100 response (95 ms to 145 ms after word onset; computed around the RMS peaks collapsed over all conditions and subjects). The reasoning behind this control analysis is that if a correlation between the Prediction Potential and the P300 was due to baseline correction or continuous activity of the Prediction Potential affecting post-word brain responses, a significant correlation should be also present with the early P100 response. Note that this control time window is suitable as it does not correlate with processes of discourse prediction, since recognizing the critical word would not yet be complete, and it is of the same polarity as the P300 component, thus not including any confound related to polarity. A similar control analysis following the same reasoning was previously performed by a study examining pre- and post-word induced activation during language processing and prediction (Grisoni et al., 2021). Additionally, we also run the correlation analysis on the bare *if* conditional, where no significant correlation is expected, to further check for the specificity of the correlation between the Prediction Potential and the P300 in the *only if* condition. Moreover, we ran the initial correlation analysis again, this time using an earlier time window of the Prediction Potential from −300 ms to −150 ms before word onset, instead of the last 150 ms directly before word onset, in order to examine any possible correlation effects in the earlier time window of the prediction potential.

To further account for potential effects driven by inter-subject variability, we built a linear mixed effects regression model modeling average word-induced potentials (from 220 ms to 480 ms past critical word onset). The model included the average Prediction Potential (from −150 ms to 0 ms before critical word onset) and Quantifier (positive / negative) as well as their interaction as fixed effects and varying intercepts and slopes for Quantifier by-subject and by-item as random effects. As an additional analysis, we ran a parallel model using average Prediction Potentials in the earlier time window (from −300 ms to −150 ms before word onset instead of from −150 ms to 0 ms) as a predictor. For both models, tests of significance were conducted as in the analyses of predictive and word-induced brain activation.

3. Results

3.1. Behavioral results

The results of the memory test after the EEG experiment, where participants had to decide whether a story was part of the experiment or not, showed that they were paying attention to the stimuli during the experiment. Due to a technical glitch, only 13 subjects were presented with the complete list of 64 memory questions (32 questions about stories that had been presented during the main experiment and 32 questions about novel stories), with an average correct rate of 71% (SD = 4.8%). The remaining 21 subjects were only presented with the 32 questions about stories that had actually been presented in the main experiment and not with the questions about the novel stories, which made the task considerably more difficult but still resulted in an average correct rate above chance level (mean = 59%; SD = 13%), thus indicating that they also paid attention to the stimuli during the experiment.

3.2. EEG results

3.2.1. Predictive neural signature of pre-activation

Scenarios with *only if* conditionals elicited a clear slow negative-going potential (i.e., the Prediction Potential), starting at about 500 ms before the onset of the critical quantifier, whereas scenarios including bare *if* conditionals did not show such a brain potential (Fig. 1A). The cluster-based permutation tests run on the time range from 150 ms to 0 ms before the critical quantifiers showed a highly significant negative cluster (p = .009), indicating differences in brain responses between the two types of conditionals. Specifically, *only if* scenarios elicited a larger Prediction Potential as compared to *if* scenarios.

To explore whether the difference in Prediction Potential is reliable even longer before the critical word, additional cluster-based permutation tests were run on a time window of 300 ms to 150 ms before word onset, also showing a significant negative cluster (p = .029). This result indicates that Prediction Potentials were significantly different already in this earlier time window, with the brain responses in *only if* trials being more negative before the critical word than in bare *if* trials.

In order to investigate the topography of these effects in more detail, and complementing the results of the permutation tests, a linear mixed-effects regression model (LMM) was built to model average brain responses in the time window of the last 150 ms before critical word onset, where significant differences were found in the permutation tests. The model showed a main effect of Connective ($\chi^2 = 8.285$; p = .003), with stronger negative brain responses in *only if* ($\beta = -0.835$, CI = [−1.543, −0.128]) as compared to *if* scenarios ($\beta = -0.013$, CI = [−0.681, 0.655]), confirming the results of the permutation tests described above. This effect of Connective did not significantly interact with any topographical factor (all p's > 0.7; a parallel model on the time window of −300 ms – -150 ms yielded the same pattern of results; see Table S1 for full model output).

3.2.2. Word-induced brain activation

Cluster-based permutation tests were performed on the word-induced brain activation separately for the negative (*none*) and positive (*one*) quantifiers, thus comparing the same quantifier across the different conditional scenarios (*if* vs. *only if*) from 200 ms to 600 ms after word onset. A significant negative cluster was found for the negative quantifier (p = .020), indicating significant differences between *if* and *only if* conditionals in the processing of negative quantifiers (*none*). No significant clusters were found for the positive quantifier (Fig. 2).

To further investigate the temporal and spatial effects of the differences between negative quantifiers appearing in the different conditional scenarios, we ran LMMs on two different critical time windows within the large time window examined with the cluster-based permutation tests, and also in a very early control time window. The time

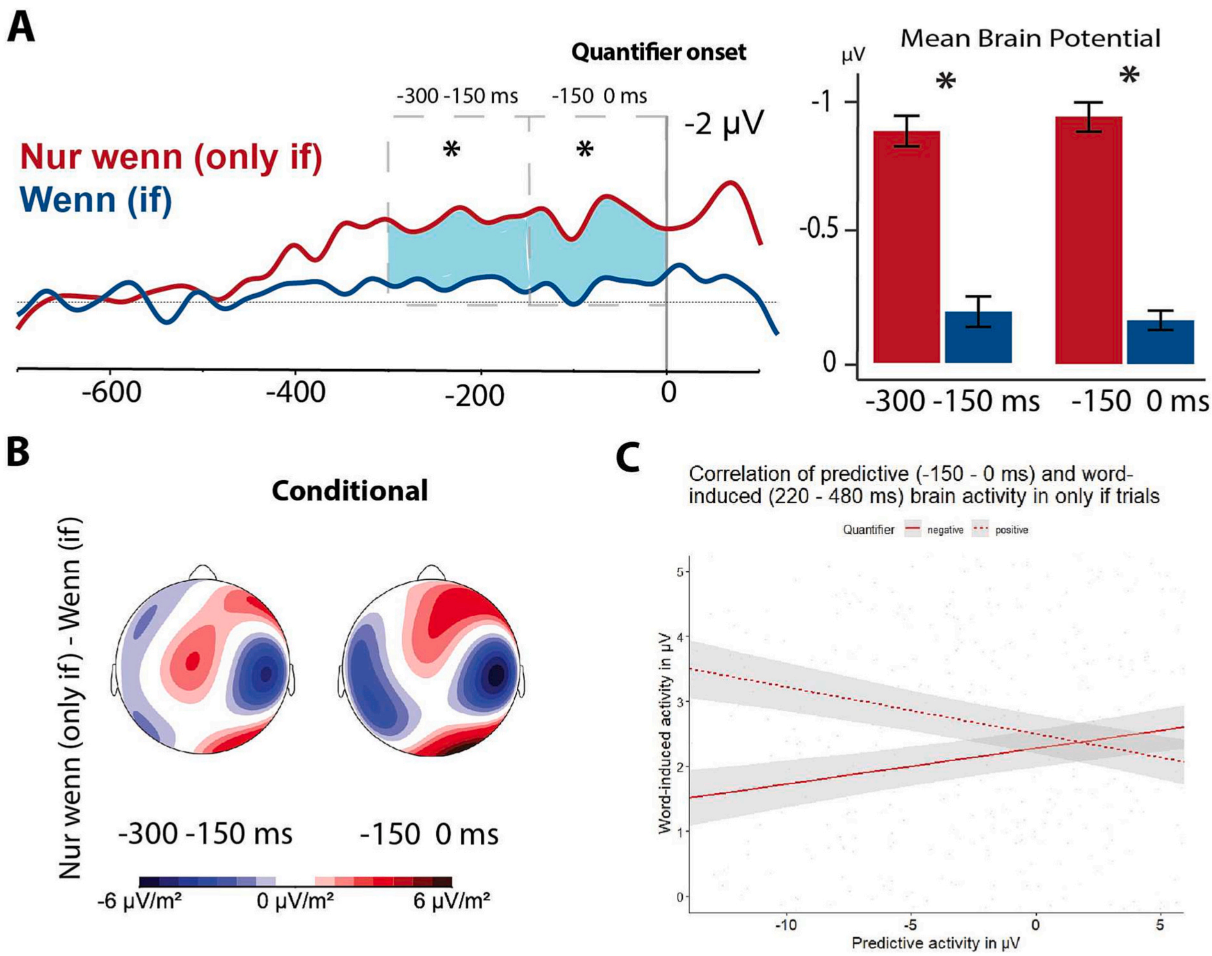


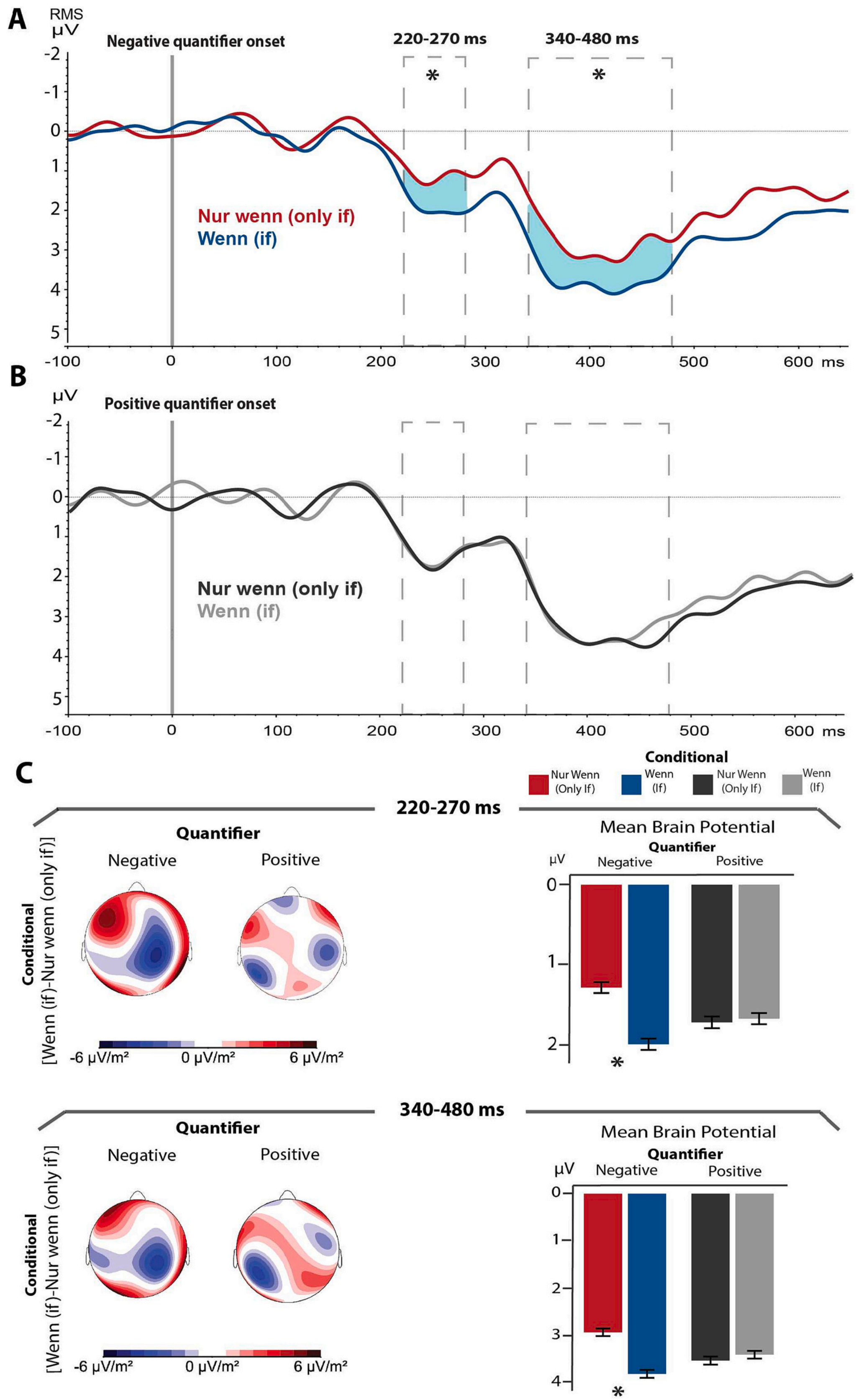
Fig. 1. A. Predictive brain activity (preceding word onset). Event-related potentials for *only if* conditionals in red and for *if* conditionals in blue. Bar plots show mean amplitudes in μV for the two types of conditionals. Asterisks and highlighted areas indicate significant differences between conditions revealed by statistical analysis. On the x-axis, 0 marks the onset of the critical quantifier (*one/none*). B. Topographic CSD (Current Source Density) maps, which estimate cortical activity after removal of volume-conduction effects, show differences of ERP distributions between conditions (*only if* – *if*) in the two tested time windows. C. Single trial correlations of mean predictive brain activity (−150 ms to 0 ms before critical word onset) and word-induced brain activity (220 ms to 480 ms after critical word onset) in *only if* scenarios. Trials with larger (more negative) Prediction Potentials prior to word onset lead to attenuated P300 responses when the expected negative quantifiers (*none*) appeared, whereas they lead to an increased P300 response when the unexpected positive quantifiers (*one*) appeared. Margins of error in gray represent one standard deviation from the mean. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

windows were defined around peaks in RMS amplitude pooled over all trials and electrodes, which were located at 120 ms, 251 ms and 426 ms after critical word onset, respectively. The very early control time window ranged from 95 ms to 145 ms, the first critical time window ranged from 220 ms to 270 ms and the second critical time window ranged from 340 ms to 480 ms after the onset of the critical quantifier. These time windows had a positive polarity and, based on their latency, we labeled them P100, early P300 and late P300 responses, respectively.

3.2.2.1. Control P100 time window – 95 ms – 145 ms. The LMM on the P100 control time window, run to investigate if the results are affected by baseline correction, yielded only a significant main effect of Laterality ($\chi2 = 30.051$; $p < .001$), with higher amplitudes in left electrodes than in midline electrodes ($p = .001$) and right electrodes ($p < .001$). The model showed no significant interaction of Connective × Quantifier ($\chi2 = 0.165$; $p = .684$) and no main effects of either Connective ($\chi2 = 0.022$; $p = .880$) or Quantifier ($\chi2 = 0.001$; $p = .997$; see Table S2 for full model output).

3.2.2.2. Early P300 time window – 220 ms – 270 ms. The LMM on the early time window of the P300 response yielded a significant main effect of Laterality ($\chi^2 = 97.952$; $p < .001$), with amplitudes being higher in left as compared to midline electrodes ($p = .021$) and again higher in midline as compared to right electrodes ($p < .001$). Additionally, a significant main effect was found for Anteriority ($\chi^2 = 13.016$; $p < .001$), with amplitudes being higher in posterior electrodes than in anterior electrodes. Importantly, the model showed a significant interaction effect of Connective × Quantifier ($\chi^2 = 30.084$; $p < .001$). To investigate the origin of this interaction, estimated marginal means were compared using the *R* package *emmeans*. In reaction to negative quantifiers, significantly larger deflections were observed in *if* than in *only if* scenarios ($F = 6.778$; $p = .009$, $d = -0.069$ (SE $= 0.026$)), while in reaction to positive quantifiers, no significant effect of Connective was observed ($F = 0.007$; $p = .934$, $d = 0.002$ (SE $= 0.026$)) confirming the results of the cluster-based permutation tests described above. Topographical factors did not significantly interact with Connective or Quantifier or both (all p's > 0.37; see Table S3 for full model output).

3.2.2.3. Later P300 time window – 340 ms – 480 ms. The LMM on the later time window of the P300 also yielded a significant main effect of Laterality ($\chi^2 = 96.203$; $p < .001$), with higher amplitudes in left electrodes than in midline electrodes ($p = .007$) and higher amplitudes in



(caption on next page)

Fig. 2. Word-induced brain activity. A. Grand average event-related potential (ERP) waveforms of negative quantifiers (*none*) in the *if* conditionals in blue and of *only if* conditionals in red. Highlighted time windows represent time windows of analysis. Asterisks indicate significant differences between the two types of conditionals. B. ERP waveforms of positive quantifiers (*one*) in *if* conditionals in gray and *only if* conditionals in black. C. On the left, topographic CSD (Current Source Density) maps, which estimate cortical activity after removal of volume-conduction effects, show differences of ERP distributions between conditions (*if* – *only if*) in each time window. On the right, bar graphs show mean ERP amplitudes by condition and time window. Error bars signify mean standard errors. Individual topographies are shown in Fig. S1. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

midline electrodes as compared to right electrodes ($p < .001$). The model showed a significant interaction of Connective × Quantifier ($\chi^2 = 42.432$; $p < .001$). Comparing estimated marginal means in negative Quantifiers showed a similar result as in the early P300 time window, namely significantly larger deflections in *if* than in *only if* trials ($F = 11.618$; $p < .001$, $d = -0.073$ (SE = 0.021)), while no significant effect of Connective was observed in reaction to positive quantifiers ($F = 0.087$; $p = .767$, $d = 0.006$ (SE = 0.021)). Topographical factors did not significantly interact with Connective or Quantifier or both (all p's > 0.45; see Table S4 for full model output).

3.2.3. Correlation results

To determine whether the observed Prediction Potential that manifested in *only if* conditionals before the onset of the critical quantifier relates to reduced P300 word-induced activation, Pearson correlations of the mean Prediction Potentials from −150 ms to critical word onset and the mean P300 word-induced potentials in the time window ranging from 220 ms to 480 ms past critical word onset were computed using single trials. These analyses were performed on a subset of fronto-central and parietal electrodes (FC5, FC6, C3, C4, CP1, CP2, P3, P4, O1, O2). Correlations of the Prediction Potentials and the P300 potentials differed significantly between positive and negative quantifiers ($z = -3.489$, $p < .001$) (Fig. 1C). Particularly, a positive correlation was found for the expected negative quantifiers (*none*) ($r = 0.065$, $p = .030$), while a negative correlation was found for the unexpected positive quantifiers (*one*) ($r = -0.085$, $p = .005$). In other words, larger negative Prediction Potentials prior to word onset are followed by reduced P300 responses after the expected negative quantifiers, but by more enhanced P300 responses after the unexpected positive quantifiers. This same pattern of results was obtained for correlations of the Prediction Potential with two smaller time windows centered around the individual local peaks from 220 ms to 270 ms and from 340 ms to 480 ms after word onset, respectively. For both time windows, correlations of the Prediction Potentials with the word-induced potentials of positive and negative quantifiers differed significantly (early time window (220 ms – 270 ms): $z = -3.004$, $p = .002$; late time window (340 ms – 480 ms): $z = -3.271$, $p = .001$). Running the same initial correlation analysis using an earlier Prediction Potential time window from −300 ms to −150 ms before word onset and the P300 time window ranging from 220 ms to 480 ms past critical word onset, correlations were also found to differ significantly between positive and negative quantifiers (z = −3.191, p = .001) in the same way as found when using the later Prediction Potential time window of the last 150 ms preceding word onset.

To check whether the observed correlation is indeed specific to the Prediction Potential and the P300 responses and as well to make sure that it is not driven by the P300 baseline correction, we ran an additional correlation analysis between the Prediction Potential and a very early P100 brain response in the time window from 95 ms to 145 ms. This time window is suitable, because it is not assumed to correlate with processes of discourse prediction, since recognizing the word would not yet be complete, and because it is of the same polarity as the P300 component (see Section 2.5.3 above for more detail). The correlations between the Prediction Potentials and the early pre-lexical P100 responses of positive and negative quantifiers did not differ significantly ($z = -1.532$, $p = .125$), indicating that the size of the Prediction Potentials did not affect these very early induced brain responses.

In order to compare the correlations in the control time window (95 ms – 145 ms) to a critical analysis time window of the same size, we conducted an additional correlation analysis between the Prediction Potential and the first peak of the P300 responses (220 ms – 270 ms). The results were consistent with the previous findings on the larger time window, with correlations between the Prediction Potential and the word-induced potentials differing significantly between positive and negative quantifiers ($z = -3.004$, $p = .002$). Parallel results were also found using an analysis time window around the second peak of the P300 response (340 ms – 480 ms: $z = -3.271$, $p = .001$).

To check whether the observed correlation is specific to the *only if* condition, we ran the same correlation tests on the bare *if* trials, where either no or a weaker Prediction Potential is expected, since in bare *if* trials participants are not expected to generate strong predictions about the upcoming discourse continuation. Indeed, in bare *if* trials, correlations of the Prediction Potentials with the P300 potentials (from 220 ms to 480 ms after word onset) of positive and negative quantifiers did not differ significantly (z = 0.706, $p = .480$), confirming that the correlation results are specific to *only if* trials.

As an alternative analysis to assess the relationship between the Prediction Potential and word-induced ERP potentials in *only if* trials, we ran a linear mixed effects regression model modeling mean word-induced potentials from 220 ms to 480 ms, with mean Prediction Potential from −150 ms to 0 ms and Quantifier plus their interaction as predictors and random effects by subject and by item. Consistent with the results obtained in the Pearson correlation tests, the model output shows a significant interaction effect of Prediction Potential and Quantifier ($\chi^2 = 37.589$; $p < .001$; see Table S5 for full model output). More negative Prediction Potentials are being followed by smaller word-induced brain responses in expected negative quantifiers ($\beta = 0.012$, CI = [−0.003, 0.028]) but by greater word-induced brain responses in unexpected positive quantifiers ($\beta = -0.057$, CI = [−0.073, −0.041]). An additional model using an earlier time window of the Prediction Potential from −300 to −150 ms as a predictor, else keeping all model specifications the same, also found a consistent significant interaction of Prediction Potential and Quantifier ($\chi^2 = 28.057$; $p < .001$; see Table S6 for full model output). Again, more negative Prediction Potentials are being followed by smaller word-induced brain responses in negative quantifiers ($\beta = 0.042$, CI = [0.024, 0.060]) but by greater word-induced brain responses in positive quantifiers ($\beta = -0.057$, CI = [−0.044, −0.008]). In parallel models on bare *if* trials, the interaction effects of Prediction Potential and Quantifier are non-significant, both using the mean Prediction Potential from −150 ms to 0 ms ($\chi^2 = 0.618$; $p = .431$) and using the mean Prediction Potential from −300 ms to −150 ms ($\chi^2 = 1.497$; $p = .221$), again finding consistent results to the Pearson correlations tests.

4. Discussion

It is broadly agreed among linguists and neuroscientists that predictions drawn from prior knowledge or contextual information can facilitate and enhance language understanding processes. Most previous work using ERP component analysis focused mainly on word-induced brain activity (i.e., brain activity observed after the critical word's onset, e.g., Szewczyk & Schriefers, 2013; Wicha et al., 2004; DeLong et al., 2005; Freunberger & Roehm, 2016), rather than on brain activity preceding the critical stimulus (see e.g., Van Berkum et al., 2005 and Federmeier, 2007, for discussions). Recently, a more direct brain indicator of prediction was discovered in studies finding highly predictive scenarios to evoke a slowly building negative ERP response that was observable prior to predictive linguistic input, the "Prediction Potential" (Pulvermüller & Grisoni, 2020). However, previous work has observed the emergence of the Prediction Potential only before predictable stimuli at the end of sentences and at the semantic level (Grisoni et al., 2017, 2021; León-Cabrera et al., 2019, 2017). A critical open question was whether such a predictive brain index can also be attested before predictable endings of discourses that span multiple sentences, where additional semantic and pragmatic processing steps are undertaken during comprehension. Furthermore, there has been little work on the relationship between the anticipatory Prediction Potential and word-induced brain potentials related to input processing, which the current paper takes the first step to address at the discourse level.

To close this gap, we conducted EEG recordings to examine differences in brain responses related to the prediction of discourse continuations, contrasting scenarios containing *only if* conditionals and bare *if* conditionals preceded and followed by identical context (*If / Only if P, Q. Not-P.*). *Only if* and *if* conditionals have distinct lexical and compositional semantics (Herburger, 2015, 2019) such that the used conditional scenarios containing *only if* would trigger stronger predictions about the continuation of the discourse than those containing bare *if*. Specifically, upon encountering a conditional statement like "*Only if the bouquets are beautiful, will I take one*", comprehenders can expect the unfolding discourse to contain one of two potential continuations, either one of the bouquets will be taken by the speaker or not. Lacking other information, these two continuations initially have approximately equal probabilities. If in the course of the unfolding discourse the antecedent of the conditional is negated (*"The bouquets are not beautiful"*), the probabilities of the two continuations included in the discourse prediction shift, as more precise expectations about the discourse continuation can be generated, with a strong preference for a negated story conclusion ("I took *none*."). To generate this prediction, both the semantic interpretation of *only if* and the contextual situation are taken into account. Finally, upon encountering the conclusion of the story (i.e., whether the speaker took one of the bouquets or not), comprehenders update their discourse representations again by integrating the novel information contained in the input. In cases where the input matches the adjusted predictions about the discourse continuation, processing costs for updating the discourse representations are reduced. If, on the other hand, the input does not match the expected discourse continuation, processing costs are increased due to the mismatch of generated expectations and encountered input. The present findings show that such an expectation about the discourse continuation is reflected in a slow negative potential, the Prediction Potential, building up in predictable scenarios (containing *only if* conditionals) from about 500 ms before the predicted critical word, and being strongest right before the onset of the predictive stimulus that encodes the discourse continuation. The emergence of a Prediction Potential in scenarios containing *only if* reflects conditional-induced prediction about the discourse continuation, which is much stronger than in the same scenarios containing bare *if* conditionals, where we found significantly weaker Prediction Potentials. This work is in line with previous examinations of predictive brain activity before the predicted upcoming word at the level of single sentences (e.g., Grisoni et al., 2021). However, our research expands on these findings by demonstrating that such predictive brain activity is also triggered by predictions at the discourse level, where understanding processes involve multiple sources of semantic and contextual-pragmatic information to generate robust predictions.

The observed Prediction Potential effect (higher predictive brain activity in *only if* as compared to bare *if* scenarios before discourse conclusions) is in line with the observed effects in word-induced brain responses. In *if* contexts, triggering weak predictions, the negated quantifier *none*, revealing the scenario conclusion, elicited an enhanced P300 brain response between 220 and 480 ms after word onset. In contrast, *only if* contexts, triggering strong predictions, showed reduced P300 responses (Fig. 2). The direction of this P300 effect mirrors the predictability of the respective discourse continuations, with the expected negated quantifier *none* revealing the scenario conclusion, being more strongly expected in *only if* scenarios as compared to bare *if* scenarios, resulting in reduced P300 activation. These results are in line with previous work showing differential activation of the P300 component in relation to integration of new information and updating of memory representations (see Polich (2007) and Nieuwenhuis, Aston-Jones, and Cohen (2005) for reviews). A more detailed analysis of the larger time window after word onset revealed two main activation peaks, one in an earlier time window from 220 ms to 270 ms after word onset and one in a later time window from 340 ms to 480 ms. While potentially different cognitive processes might be related to each of these two peaks, the statistical analyses of the present data showed the same pattern of results in both main effects and interactions of the factors of interest (Connective × Quantifier) for both time windows. We thus treated the two activation peaks as behaving similarly and cannot draw any major conclusions about differential underlying processes here. Overall, the P300 was attenuated in *only if* scenarios in predictable discourse continuations (*Not Q.*) relative to the same continuations in bare *if* scenarios, indicating that predictable discourse continuations lead to facilitation in discourse continuation processing. The word-induced brain responses elicited by the positive quantifier *one* were not found to differ between the types of conditionals.

These findings complement evidence of previous work using similar materials, which found differences in reading times of the scenario conclusion between the different types of conditionals during self-paced reading (Barthel et al., 2022). In that study, negated quantifiers revealing the scenario conclusion (*Not Q.*, e.g. "*He took none.*") were read faster in *only if* scenarios than in bare *if* scenarios. The obtained EEG results match these previous findings and support previously proposed linguistic analyses of the meaning of *only if* vs. *if* conditionals (Herburger, 2015, 2019), suggesting that readers interpret *only if* conditionals as entailing '*If not P, not Q.*', e.g. "*If the flowers are not beautiful, he won't take them.*". This is reflected in reduced processing effort in comprehending a negated conclusion (*Not Q.*) in *only if* scenarios as compared to in bare *if* scenarios that contained the negation of the conditional's antecedent (*Not P.*, e.g. "*The flowers were not beautiful.*"). Bare *if* scenarios, on the other hand, are generally interpreted as '*If P, Q.*', e.g. *"If the flowers are beautiful, he'll take them."*, not allowing for a strong prediction of a scenario conclusion after the presentation of a negated antecedent of the conditional (*Not P.*). Our results confirmed this, as scenarios containing bare *if* conditionals showed no predictive brain activation prior the word onset and an enhanced P300 response, suggesting more effortful processing during the comprehension of the scenario conclusion, which aligns with the prolonged reading times reported in the self-paced reading study (Barthel et al., 2022).

A remaining critical question is whether the reduced processing effort in the integration of the presented discourse conclusion, as suggested by the reduced P300 effect, is indeed due to the presence of predictive activity before the onset of the critical word, or put differently, whether the observed Prediction Potential and the word-induced P300 are functionally related. To address this point, we examined the relationship between the two ERP components in *only if* scenarios using correlation analysis on single trial data. The results reveal that larger anticipatory Prediction Potentials lead to decreased P300 word-induced activation when encountering expected negative quantifiers (*none*). Notably, for unexpected, positive quantifiers (*one*), on the other hand, larger Prediction Potentials lead to increased P300 word-induced activation (Fig. 1C). These findings suggest that stronger predictions of discourse continuation, reflected in the preactivation of neural traces of a discourse continuation before the expected word, facilitate the processing of the encountered input, as reflected in a reduction of the P300 word-induced responses. This correlation is in line with a previous study showing such a functional relationship between pre- and post-word neural processing (Grisoni et al., 2021). However, here we critically add and show that larger Prediction Potentials lead to reduced P300 responses when the input matches the prediction, indicating facilitated processing and integration. In cases where the input does not match the prediction, on the other hand, larger Prediction Potentials lead to increased P300 responses, suggesting higher processing costs.

The functional relationship between these brain indicators of prediction and discourse processing finds further support by additional control analyses showing that the correlation is specific to the P300 component, as it was found to be absent between the Prediction Potential and the very early P100 component, a finding that is consistent with a previous study on semantic processing (Grisoni et al., 2021). The absence of a correlation with the early P100 component further strengthens the case for the relationship of the Prediction Potential and word-induced discourse processing, since any potential spurious influences of baseline corrections or possible extensions of the slow wave Predictive Potential into post-word regions should also be evident in the P100 component, as it is directly adjacent to the Prediction Potential. Furthermore, a significant correlation was only found for *only if* scenarios but not for *if* scenarios, further speaking to the specificity of the relationship between the Prediction Potential and word-induced processing. Overall, this evidence for a direct link between pre-activation of expected discourse continuations and reduced costs of input processing sheds light on the functional role of different neural signatures of prediction in language comprehension, demonstrating that the mental processes of discourse understanding are functionally interconnected with processes of discourse prediction. Future research is required to scrutinize this relationship across various linguistic tasks and dimensions, including semantics, syntax, and phonology, to determine whether the patterns observed in the present study manifest consistently across these different levels of language processing.

A final observation that could be tackled by further studies is the presence of word-induced P300 effect instead of a (similarly conceivable) N400 effect, which is typically observed in case of semantic violation or low predictability. A possible reason for the absence of an N400 effect is that the ERPs in the present study were time-locked to functional words, whereas N400 effects found in language processing typically involve processing difficulty of lexical (content) words (e.g., Holcomb, Kounios, Anderson, & West, 1999; Kutas & Federmeier, 2011; Kutas & Van Petten, 1994; Lau et al., 2006; Nieuwland & Van Berkum, 2006). In our study, both contrasted discourse continuations (positive and negative quantifiers) are both syntactically and semantically well-formed. The built-in congruence and incongruence between the critical final sentence and discourse requires the processing of 1) the semantics of the negative quantifier (*none*), 2) the compositional semantics and truth value of the sentence (*Not Q.*), and 3) the discourse context (*If / Only if P, Q. Not P.*). All the three processes can give rise to processing costs, and since negation out of context is known to be costly (Kaup & Dudschig, 2020), any potential differences in the N400 window due to 3) might have been diminished by the costs of 1) and/or 2). Note also that effects in the P300 component have been shown to be elicited by the absence or presence of a prediction match, specifically when the target words play a crucial role in performing a categorization task with a binary choice (Alday & Kretzschmar, 2019). This parallels the processing and binary categorization of discourse continuations in the conditional scenarios used here, and might be a further explanation why a P300 and not a N400 was observed in the present study. While these serve as possible explanations, additional studies are needed to further clarify under which precise conditions a P300 effect or an N400 effect can be expected to be more likely in discourse-level language prediction research, as well as whether and how they might be related.

5. Conclusion

Short stories with more versus less predictable continuations, depending on the kind of conditional connective (*if* vs. *only if*) they contained, triggered more versus less predictive brain activity prior to their conclusion. Specifically, highly predictable stories that contained *only if* conditionals triggered a clear brain response prior to the onset of the critical word, the so-called Prediction Potential. In contrast, such a Prediction Potential was absent in less predictable stories containing bare *if* conditionals. Furthermore, word-induced brain activity triggered by the presentation of the critical word showed an enhanced P300 component in less predictable discourses as compared to highly predictable ones. Intriguingly, these brain indicators of predictive and word-induced activities were found to be correlated, with stronger predictive activity leading to reduced word-induced brain activity in predictable discourse continuations and to increased word-induced brain activity in unpredictable discourse continuations. The present findings deepen our understanding of language processing and prediction at the discourse level, highlighting the functional link between discourse understanding and prediction processes.

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CRediT authorship contribution statement

Mathias Barthel: Methodology, Software, Formal analysis, Investigation, Data curation, Visualization, Supervision, Conceptualization, Writing - original draft, Writing - review & editing. **Rosario Tomasello:** Methodology, Formal analysis, Software, Investigation, Visualization, Supervision, Writing - original draft, Writing - review & editing. **Mingya Liu:** Conceptualization, Methodology, Formal analysis, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

Authors have no competing interests to declare.

Data availability

Averaged and segmented data and analysis scripts are available on OSF under https://osf.io/264f8/.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cognition.2023.105635.

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