Syntactic Constructions Drive Cortical Tracking in the Absence of Lexical Content: An Electrophysiological Investigation of Sentence Processing During Reading

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Abstract

It has been suggested that the synchronization of neural oscillations to syntactic units, such as phrases or clauses, is dependent on lexically-derived projections of syntactic structure. This assertion is based from recent evidence that participants are unable to effectively track syntax when listening to jabberwocky sentences, in which content words are replaced with pseudowords thereby eliminating lexically-derived syntactic projections (Kaufeld et al., 2020; Coopmans et al., 2022). In the present study, we present evidence that participants can in fact track syntactic units in jabberwocky sentences when the stimuli are presented visually and in a syntactic pattern with high cue validity – methodological differences that make it easier for participants to identify syntactic patterns. We interpret this finding as indicating that the primary driving force of cortical tracking is pattern recognition and temporal predication of said pattern and that this pattern need not derive from lexical projections.

Keywords: neural synchrony, oscillations, EEG, syntax, language comprehension

Introduction:

It has been suggested that the firing of neural oscillations can temporally synchronize with the occurrence of multi-unit linguistic representations (e.g., syntactic constituents such as phrases or clauses) (Martin, 2020; Martin & Doumas, 2017; Meyer et al., 2019, 2020). Experimental evidence for this was first demonstrated by Ding and colleagues (Ding, Melloni, Tian, et al., 2017; Ding, Melloni, Yang, et al., 2017; Ding et al., 2016) using a frequency-tagging paradigm in which participants' neural responses to monosyllabic words were enhanced when word boundaries co-occurred with phrase and sentence boundaries.

In subsequent work, Kaufeld et al. (2020) and Coopmans et al. (2022) further explored the effect in naturalistic speech using mutual information (MI) analyses. Both studies demonstrated that the effect could be found in forward audio sentences, but not in sentences in which the audio had been reversed. Coopmans et al. additionally demonstrated that while sentences show the highest level of neural synchrony, the difference was not significantly greater than for idioms and syntactic prose (syntactically correct, but semantically anomalous sentences). Conversely, sentences evidenced significantly higher neural synchrony than did word lists and jabberwocky (sentences wherein content words are replaced with pseudowords while function words and morphemes are retained). This last finding is of particular interest to the current study since it suggests that content words may be required during the processing of syntax. Indeed Coopmans et al. suggest that the pattern of differences indicates that phrasal syntax relies on lexically-driven computation of syntax thereby providing support for lexically-based models of syntactic processing (e.g., Hagoort, 2013; Hagoort, 2017; Matchin & Hickok, 2019).

This last finding is somewhat at odds with the results of a recent study by Rafferty et al. (2023) who used a minimal phrase paradigm to investigate whether individual noun phrases composed of a determiner and a pseudoword were sufficient to elicit neural synchrony given the lack of lexical semantics. This study recorded EEG activity while participants read mixed blocks of syntactically well-formed phrases composed of a determiner and a pseudoword (*the moop*) and a wordlist condition composed of the same pseudoword followed by a determiner (*moop the*). Results showed that in comparison to the words condition, there was significantly greater neural synchrony (measured by inter-trial phase coherence) at the phrase rate with no difference between conditions at the word rate, suggesting that the minimal phrases were sufficient to induce neural synchrony even when they contained no content words. If Coopmans et al. are correct in suggesting that lexical projections are required for syntax, it is not clear how Rafferty et al.'s stimuli, which do not include real words capable of projecting a syntactic schema, also elicited neural synchrony at the phrase rate.

Accordingly, we suggest an alternative, somewhat broader interpretation of the effects; namely, that cortical tracking of syntax depends on pattern recognition and temporal prediction of said pattern but does not *require* lexical projections. Syntactic patterns may derive from lexically-based models as suggested by Hagoort (2013; 2017) and Matchin & Hickok (2019), but they can also derive from other linguistic sources such as non-lexically based syntactic constructions (e.g., Goldberg, 2006), or prosodic patterns associated with syntax (Frazier et al., 2006; Glushko et al., 2022). In the case of Rafferty et al.'s findings, for example, the occurrence of a determiner is a reliable syntactic cue for

the subsequent occurrence of a noun (given past experience with the argument structure of English grammar). Why, then, does this effect not surface in the jabberwocky sentences used by Kaufeld et al.'s and Coopman et al.'s studies? The critical difference is that both studies present their stimuli auditorily in running speech whereas Rafferty et al. used a visual paradigm. As a result, it appears that participants were crucially unable to track the utterances at the word level. In fact, Kaufeld et al. report that tracking at the word rate is significantly better for sentences than for jabberwocky ($\beta = 0.48$; $p < 0.01$) and nearly significantly worse for jabberwocky than for word lists ($\beta = -0.33$; $p = 0.06$). In comparison, tracking at the word rate between sentences and the word list condition shows no significant difference ($\beta = 0.16$; $p = 0.14$). Since it appears that participants were unable to parse individual words from the jabberwocky speech stream, they would consequently have been unable to track phrases since phrase tracking presupposes word tracking.

Whether syntax *requires* lexical projections is an important question that affects how we understand the nature of syntax, as well as that of cortical synchrony. Construction approaches to syntax (Goldberg, 2006), for example, argue that syntactic constructions may be defined as syntactic patterns or templates that carry their own meaning independent of the meaning of the lexical items that fill the template. Psycholinguistic evidence would seem to support this possibility (Allen et al., 2012; Bencini & Goldberg, 2000; Adele E. Goldberg, 2006; M. A. Johnson et al., 2016; Kako, 2006; Kaschak & Glenberg, 2004). For example, Kaschak and Glenberg (2004) found that speakers use syntactic constructions to derive the meaning of novel denominal verbs. If the verb occurred in the ditransitive construction (e.g., *She crutched him the apple*), for example, participants concocted a transfer-related meaning for the verb (i.e., she used the crutch to transfer the apple from her possession to his possession). If the verb appeared in the transitive construction (e.g., *She crutched him*) they interpreted the sentence to mean that she hit him over the head with a crutch. Casenhiser and Goldberg (2005) demonstrated that children were able to learn the meaning associated with a novel syntactic construction even which the verb appearing in that construction was novel. Van Dam and Desai (2016) demonstrated that even after controlling for verb semantics, the caused-motion construction (cf., Goldberg, 1995), whose meaning is associated with motion, still elicits sensory-motor activation. Thus, there is some evidence that syntax may comprise a linguistic pattern independent of specific lexical items. To be clear, we agree that lexical projections may in fact form patterns that are used in syntactic processing, but we suggest that they are not a *sine qua non* of syntactic processing.

To further clarify whether tracking of phrases requires lexically driven computation of syntax, we investigated whether predictable syntactic frames would elicit synchrony in the absence of lexical content. To establish syntactic predictability, sentence stimuli were composed of syntactically identical English and jabberwocky sentences using the English caused-motion construction (Goldberg, 1995). We chose the caused motion construction because of the high cue validity of its syntactic structure and meaning (cf. Goldberg et al. 2005, Goldberg 2006). Its pattern is represented below using constructionist conventions. Note that both syntactic and semantic specifications are part of the pattern.

NP<AGENT> V<CAUSAL MOTION> NP<THEME> PP<PATH/LOCATION>
The man<AGENT> *pulled*<CAUSAL MOTION VERB> *the boat*<*THEME*> *down the dock*<*PATH/LOCATION*>

To control for effects related to semantic composition in the English sentences, participants read scrambled wordlists with the same lexical items, constructed to minimize coherent syntactic structure. To control for both semantics and syntax at once, we also included a pseudoword wordlist control condition. All stimuli were presented visually using rapid serial visual presentation to ensure that between-condition differences in phrase-level tracking did not result from ambiguous word boundaries in the items containing unfamiliar pseudowords. Example stimuli can be seen below in Table 1.

As in Kaufeld et al. and Coopmans et al., we quantified the degree of neural synchrony as the degree of MI between EEG recordings and the syntactic structure of the sentences. Should the composition of syntactic structure necessitate the presence of lexical-syntactic projections, English sentences would elicit greater synchrony (as evidenced by greater MI) than all other conditions. We hypothesize, however, that predictable syntactic patterns are sufficient to elicit phrase-level tracking. As a result, we anticipate that both English and jabberwocky sentences should elicit greater MI than both English and pseudoword wordlist conditions.

To preview our results, we find that participants were able to track phrases in both English and jabberwocky sentences to a similar degree, whereas considerably less phrase-level tracking was observed for the two wordlist conditions. These results are consistent with prior studies showing that neural oscillations may become synchronized with the boundaries of syntactic phrases. However, unlike previous work, our findings suggest that such boundaries may be inferred independently of lexical projections, provided that the syntactic frame employed is sufficiently predictable and recognizable.

Table 1: Example stimuli from each condition.

	Example Stimuli
English Sentence	the man pulled a boat down the dock
Jabberwocky Sentence	the dex mooped a pob down the jarm
English Wordlist	boat the a man dock down pulled the
Pseudoword Wordlist	pob the a dex jarm down mooped the

Method

Participants

25 native English speakers (16 females & 9 males) aged 20-34 (M = 24.32; SD = 3.69) were recruited for this study. Participants had normal or corrected to normal vision and no reported history of neurological injury or pathology. All participants were right-handed as assessed by the Edinburgh Handedness Inventory (Oldfield, 1971). This study was approved by the Institutional Review Board of the University of Tennessee Health Science Center. Prior to the experiment, participants provided signed informed consent on a document approved by the Institutional Review Board.

Materials

Four sets of sentence stimuli were constructed. The first set consisted of 20 grammatical English sentences that adhered to the structure of the caused-motion construction (e.g., *The man pulled a boat down the dock).* That is, each sentence included a subject noun phrase, and a verb phrase with direct object and prepositional phrase. We also constructed 20 lexically matched English word lists by pseudo-randomizing order of the words within the English sentences to reduce global syntactic structure. All words were a single syllable, morphologically regular, and no longer than 7 letters. We then constructed 20 jabberwocky sentences, which contained the same syntactic structure but where content words were replaced with pseudowords. Pseudowords were created by swapping one letter from real English words. We controlled for phonotactic probability by first calculating the summed phonetic probability and bi-phone probability for each pseudoword using the online phonotactic probability calculator from the University of Kansas (Vitevitch & Luce, 2004). Then we compared these summed totals (M = 1.173, SD = 0.0605) to their real-English counterparts (M = 1.176, SD = 0.0508) using paired-samples t-tests. No significant effects were found, $t(1,59) = -0.5158$, $p = 0.608$. To control for lexical-semantics and syntactic structure, we also constructed a pseudoword wordlist condition.

Procedure

For EEG recordings participants sat in a comfortable chair approximately 50 inches away from a television monitor in a magnetically shielded, double-walled, sound-attenuating booth. Stimuli were presented visually to reduce effects of overt prosody present in the audio signal.

Each trial was preceded by a 1000ms period during which the monitor screen showed a fixation cross in its center to bring participants' focus to the center of the screen and eliminate any saccadic activity associated with trial onset. After this period, the fixation cross disappeared, and sentences were presented one word at a time. Each word was visible on the screen for 500ms, after which it was immediately replaced by the next word. Participants were instructed to read the sentences silently. 1000ms after the offset of the sentence-final word, participants heard a beep to indicate that they should press a button on a hand-held controller to advance to the next trial. For an example timeline, see *Figure 1.*

The experimental procedure was divided into eight mixed blocks. Each block consisted of 40 randomized experimental trials, with 10 from each condition. No more than three items from one condition occurred in sequence, and block order was randomized across participants. Blocks lasted approximately 7 minutes each, for a total of approximately 1 hour in the EEG booth.

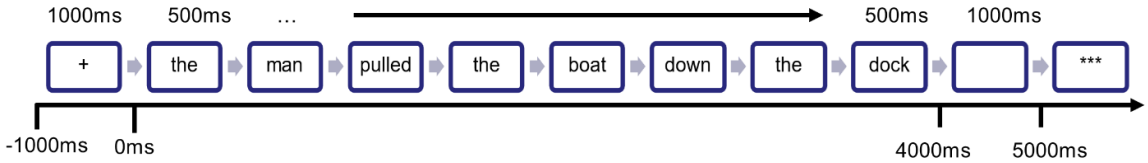

Figure 1: Trial timeline.

EEG Acquisition

EEG data were recorded at a sampling rate of 1000Hz using 64 electrodes mounted on an unlinked and sintered NeuroScan QuikCap 64, configured according to the extended international 10-20 system (Klem, 1999). Horizontal eye movement was recorded by placing electrodes on the lateral canthi of each eye (horizontal electrooculography—HEOG); meanwhile, vertical eye movement was recorded by placing electrodes on the superior and inferior orbit (vertical electrooculography VEOG) of the left eye. Electrocardiography (EKG) was recorded from bipolar electrodes placed on both sides of participants' neck once their pulse was located.

EEG Pre-processing

Data were preprocessed offline using the open-source FieldTrip toolbox (v20200801; Oostenveld et al., 2011) in MATLAB (The MathWorks, Inc., Matick, MA, USA). Continuous EEG data were first bandpass filtered between 0.1 and 100 Hz (1st order, two-pass Butterworth), and 60Hz line-noise was then removed using the fast-Fourier transform. Data were then epoched from -3000ms to +6000ms relative to stimulus onset. Trials with response times that were less than 100ms were removed. Next, we visually inspected the single trial data and removed noisy channels (M = 1.6; SD = 1.32). Data were then re-referenced to the common average, and trials with clear movement artifacts were removed. We removed ocular and cardiac artifacts using independent components analysis. We then applied the resultant component weights to the original data and subtracted the artifacts. On average 2.6 components were removed per participant. Using the cleaned data, we interpolated noisy channels previously removed using the 'spline' method. We conducted a final manual inspection of all trials and removed any remaining artifactual trials. On average, subjects maintained > 58 trials per condition (SD = 10.95).

Mutual Information

To investigate whether predictable syntactic frames would elicit neural synchrony, we calculated mutual information (MI) between the EEG and vector representations of abstract syntactic structure at the frequency of occurrence for phrases (.75Hz) (Brodbeck et al., 2018; Coopmans et al., 2022). We selected MI for comparability to Kaufeld et al. and Coopmans et al. Pairing MI with vector representations of sentence structure allowed us to assess cortical tracking of phrases that occur non-metrically. Vectors were created manually by first identifying all time samples that corresponded to phrase final words in each sentence. We then coded each of these samples as ones to represent the closure of syntactic constituents or "nodes". All other samples were coded as zeroes (see *Figure 2a*). The same vectors of syntactic structure were evaluated in the MI analysis for all conditions under the assumption that cortical responses to wordlists should demonstrate low MI with the structure vectors since the wordlists do not contain internal syntactic structure.

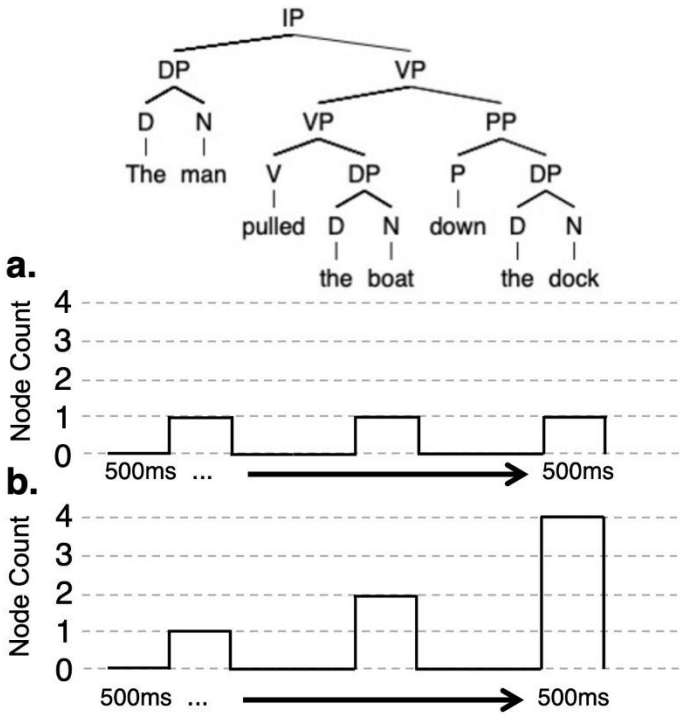

Figure 2: Visual depictions of a. vectors encoding the closure of syntactic nodes according to the phrase structure of the sentence and b. vectors encoding the number of syntactic phrasal nodes that are closed by a given item (i.e., "node count") according to the phrase structure of the sentence.

To ensure that unequal trial counts did not bias mutual information values, we randomly selected an equal number of trials across all conditions based upon the minimum number of trials remaining for each condition. We then selected a subset of centro-parietal electrodes (C3, CZ, C4, CP3, CPZ, CP4, P3, PZ, P4) for all additional analysis steps, based on previous work showing that cortical tracking of speech results in scalp topographies with centro-parietal foci (e.g., Kaufeld et al. 2020, Coopmans et al., 2022). Following this, we band-pass filtered the data into frequencies corresponding to the rate of occurrence for phrases (0.65 - 0.85Hz, centered around the phrase rate of .75Hz), separately for each condition (3rd order, two-pass Butterworth). We then Hilbert-transformed the data and normalized the resulting real and imaginary-valued coefficients separately using the Gaussian copula method (Ince et al., 2017). The resulting phase and power time series for each trial were then recombined and trimmed to be equal in length to the syntactic vectors described above, which were added to the data structures for each condition as "dummy" sensors. We then concatenated all trials end-to-end and calculate MI for each condition as:

$$MI = H(\text{Speech}) + H(\text{EEG}) - H(\text{EEG, Speech})$$

where H(Speech) is the Shannon entropy of the Hilbert transformed speech envelope/syntactic structure, H(EEG) is the entropy of the Hilbert transformed EEG, and H(EEG, Speech) is their joint entropy. As in previous works, we calculated MI at 5 different lags from 60-140ms and averaged across them to account for potential delays in brain response that could develop across the length of the study (Keitel et al., 2018;

Kaufeld et al., 2020). We then log-transformed the data and removed outliers whose MI values were in the 2.5th and 97.5th percentiles.

While our analysis of node closure captures the formation of syntactic phrases at the local level, syntactic structure encodes information about hierarchical relationships amongst multiple constituents across the length of a sentence (Brennan & Hale, 2019). Thus, in addition to assessing cortical tracking of node closures, we also computed MI between the EEG and abstract vectors that encode the accumulated number of syntactic constituents that each phrase-final word completes—i.e., node count (Brennan & Hale, 2019; Coopmans et al., 2022; Lo et al., 2022; Nelson et al., 2017). For this, we copied the binary vectors created above and coded all non-zero samples with the number of phrasal nodes that may be closed at that point in time. Visual depictions of the vectors corresponding to node count can be seen in *Figure 2b*.

With this analysis, we investigated the possibility that the presence of intact grammatical structure in jabberwocky items may allow for phrase formation at the local level, but utterance-spanning constituents may require the ability to associate thematic roles with specific items. If this is the case, we expected that MI for English and jabberwocky sentences would not differ when considering node closure but would differ when considering node count. Alternatively, the semantics associated with the caused-motion construction may license the formation of such hierarchical syntactic relationships. If this is the case, we anticipated no differences between English and jabberwocky sentences related to tracking node count.

Statistical Analysis

We used the *afex* package (Singmann et al., 2023) in R (R Core Team, 2021) to fit linear mixed models (estimated using REML and the *nloptwrap* optimizer; Baayen et al., 2008) to assess whether condition predicted MI between EEG and abstract representations of syntactic structure that encoded syntactic node closure and node count. Condition was treated as a fixed-effect and was treatment coded with English sentences set as the reference level. Random-effects structure consisted of by-participant random intercepts. Standardized parameters were obtained by fitting the model on a standardized version of the dataset. 95% Confidence Intervals (CIs) and *p*-values were computed using a Wald *t*-distribution approximation, with the threshold for significance set at $p = 0.05$. Potential violations of sphericity were accounted for using Greenhouse-Geisser correction. Subsequent pairwise comparisons were conducted using estimated marginal means from the *emmeans* package in R with Tukey's method for multiple comparisons (Length, 2018).

Results

In this study, we evaluated whether syntactic frames were sufficient to elicit neural synchronization in the absence of lexical content. For this, we calculated MI between abstract representations of syntactic structure and EEG data that was recorded as participants read English sentences, jabberwocky sentences, English wordlists, and pseudoword wordlists. We assessed whether condition was a statistically significant predictor of MI using a linear mixed-effects model. Results for the model predicting MI for node closure indicated that condition was a significant predictor of MI ($F(2.85, 68.43) = 14.15$, MSE = 0.24, $p < 0.001$). Estimated marginal means indicated that MI for

English sentences (M = -4.61, SE = 0.1073) was significantly higher than that for English wordlists (M = -5.07, SE = 0.1012, $p = 0.006$) and pseudoword wordlists M = -5.21, SE = 0.1049; $p > 0.001$). Jabberwocky also sentences elicited significantly greater MI (M = -4.46, SE = 0.0969) than both the English $p = 0.002$) and pseudoword wordlist conditions $p > 0.001$). No significant differences were observed between English and jabberwocky sentences $p = 0.7221$) or English and pseudoword wordlists $p = 0.6867$).

The model predicting MI for node count indicated that condition was again a significant predictor of MI ($F(2.30, 55.28) = 23.17$, MSE = 0.30, $p < 0.001$). Estimated marginal means indicated that MI for English sentences (M = -4.92, SE = 0.0974) was significantly higher than that for English wordlists (M = -5.48, SE = 0.1037, $p = 0.007$) and pseudoword wordlists (M = -5.77, SE = 0.1403; $p = 0.002$). Jabberwocky also sentences elicited significantly greater MI (M = -4.479, SE = 0.0860) than both the English ($p = 0.001$) and pseudoword wordlist conditions ($p > 0.001$). No significant differences were observed between English and jabberwocky sentences ($p = 0.76574$) or English and pseudoword wordlists ($p = 0.2748$). Results are depicted Figure 3.

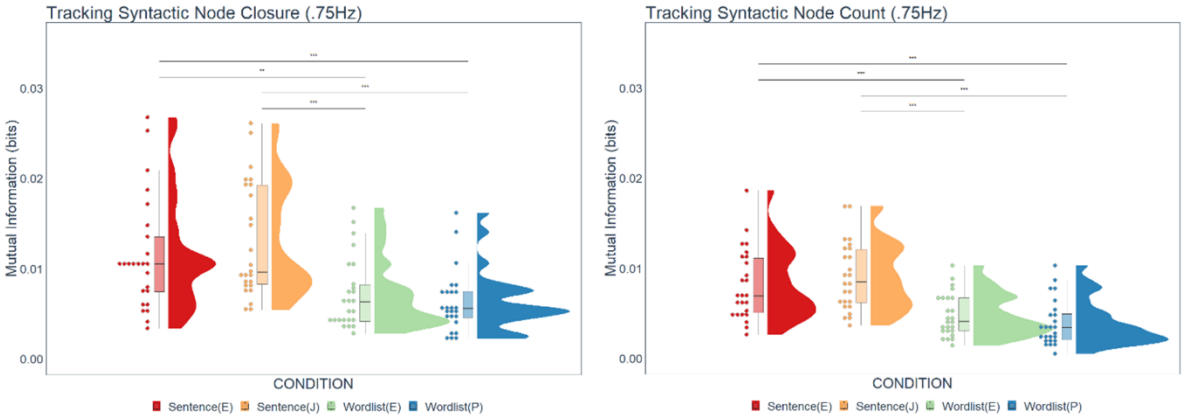

Figure 3: (left) MI between EEG responses at the rate of phrases (.75Hz) and vector representations of syntactic node closure. (right) MI between EEG responses at the rate of phrases (.75Hz) and vector representations of syntactic node count. Significant differences between conditions are denoted with * for $p < 0.05$, ** for $p < 0.01$, and *** for $p < 0.001$.

Discussion

In this study we set out to test whether the brain could track purely syntactic units when content words are replaced with pseudowords resulting in a linguistic pattern that would have to be inferred from the syntactic form without recourse to lexical projections. Our results are consistent with our previous findings reported in Rafferty et al. (2023). Relative to wordlists that lack syntactic structure, we observed greater MI at phrase boundaries for both English and jabberwocky sentences, both of which adhere to the English caused-motion sentence structure. We found this general pattern to hold both when analyzing MI for node closures as well as when analyzing MI for node count across the sentence. MI analysis of node closures suggests that participants can track phrase-level units of English and jabberwocky, while the node count analysis suggests that

participants can track the whole of the caused-motion construction whether in English or jabberwocky.

The results of the experiment provide further evidence that neural synchrony drives the recognition of endogenous syntactic patterns in the absence of exogenous stimuli. Our findings do diverge, however, from conclusions drawn from recent neuroimaging studies. In particular, Kaufeld et al. and Coopmans et al. found that jabberwocky sentences showed significantly less neural synchrony than did English sentences. Using visual presentation, in which words are easily separable from one another, seems to have eliminated this difference and enabled participants to successfully track phrases within the jabberwocky sentences. There was in fact no significant difference in neural synchrony at the phrase rate between the jabberwocky and English sentence conditions, nor at the word rate for pseudoword and English wordlist conditions. Given the important difference in stimulus presentation, we believe that the present results are reconcilable with the findings of Kaufeld et al. and Coopmans et al. Indeed, Coopmans et al. do point to the difficulty of parsing pseudowords from the speech stream, although their interpretation of the finding in light of syntactic theory is more lexicalist than our own perspective. That increased MI at phrase boundaries is observable for sentences composed of both real words and pseudowords suggests that the effect need not be driven by lexically derived projections of argument structure but is instead driven by predictability that in this case is generated by the syntactic pattern of the caused-motion construction.

Outside of the context of reading, processing of a naturalistic speech stream is arguably a more ecologically natural paradigm for examining cortical tracking of sentences than is the well-controlled timing inherent in the visual presentation of stimuli in the present experiment. On the other hand, it is also arguable that jabberwocky sentences that make it difficult for listeners to parse words from the speech stream also have limited ecological naturalness since that situation may be rare in natural contexts. Even infants may rarely encounter such a situation since they are known to be able to take advantage of various factors to determine lexical boundaries including coarticulation and stress (E. K. Johnson & Jusczyk, 2001), prosody (E. K. Johnson et al., 2014; Kim et al., 2012), stress (Hay & Saffran, 2012), and transitional probabilities (Saffran, Aslin, et al., 1996; Saffran, Newport, et al., 1996). Thus, perhaps neither paradigm accurately represents a typical language processing situation.

Nonetheless, both sets of studies point to an important aspect of syntactic processing. Namely, that a prerequisite of processing syntactic structures is the ability to identify the units of the structure that are to be combined (e.g., words or at the very least slots into which words conforming to the specifications of a syntactic pattern might fit). Our findings suggest that these units need not be previously known words, however. In fact, this may be an important feature of language since it allows language learners to leverage their understanding of phrase and clause level syntactic pairings between form and meaning to deduce the meaning of novel words (e.g., (Fisher et al., 2010; Gleitman, 1990; Adele E. Goldberg, 2006; Landau & Gleitman, 1985; Lee & Naigles, 2005). Although the present study does not negate the possibility that argument structure may project from stored lexical items, it does suggest that syntactic structures may be defined without such projections. Syntactic representations may be stored as abstract patterns wherein the slots are filled with linguistic components (e.g., morphemes, words, phrases

etc.) that conform to the specifications of the pattern. In the present study, we employed a syntactic construction whose form and meaning have low ambiguity, made even more predictable by being repeated multiple times over the course of the experiment. As a result, listeners appear to have been able to make use of this pattern to parse the sentences they heard even when the sentences were composed of jabberwocky words, rather than known English words.

We must acknowledge that the present results were obtained in a tightly controlled experimental paradigm that uses visual presentation of stimuli. The observed effect may be a product of the experimental context rather than the natural behavior of the language comprehension system. Specifically, our visual stimuli were presented at a constant rate of one word every 500ms, which is considerably slower than the typical reading rate for an adult. It is also the case that reading rates typically fluctuate across sentences speeding up for certain words and/or at certain parts of a sentence and slowing down for others. Thus, our results may not reflect the processes that take place during self-paced reading. Future research may seek to conduct studies while recording simultaneous eye-tracking along with EEG.

Finally, Coopmans et al. suggest that the parsing is accomplished "in service of semantic composition". That is, syntax is not parsed for the sake of syntax alone, but in order to construct meaning. Similarly, several studies from the Fedorenko lab (Fedorenko et al., 2020; Fedorenko et al., 2016; Mollica et al., 2020) have suggested that processing both syntax and semantics elicits a much more robust neural response in listeners. The caused motion construction used in the present study assigns clear semantic roles to the slots in the pattern allowing participants to derive meaning from the jabberwocky sentences in spite of the lack of lexical content. It would be interesting to explore whether the same effect would be found for a syntactic pattern that did not have such obvious (or any) semantic roles.

Conclusion

The ability to infer syntactic representations from language input is central to comprehension. Neurophysiological evidence suggests that this ability may be supported by the synchronous firing of low-frequency neural oscillations, aligned with the occurrence of grammatical phrases. In this study, we showed that such patterns of oscillatory synchronization may be elicited by predictable syntactic templates in the absence of recognizable lexical content. These findings bridge recent neuroimaging findings with contemporary psycholinguistic data on syntactic representation.

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