Individual differences in neural markers of beat processing predict spoken grammar skills in six-year-old children

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Abstract

Based on the idea that neural entrainment establishes regular attentional fluctuations that facilitate hierarchical processing in both music and language, we hypothesized that individual differences in syntactic (grammatical) skills will be predicted by patterns of neural responses to musical rhythm. To test this hypothesis, we recorded neural activity using electroencephalography (EEG) while children ($N = 25$) listened passively to rhythmic patterns that induced different beat percepts. Analysis of evoked beta and gamma activity revealed that individual differences in the magnitude of neural responses to rhythm predicted variance in six-year-olds' expressive grammar abilities, beyond and complementarily to their performance in a behavioral rhythm perception task. These results reinforce the idea that mechanisms of neural beat entrainment may be a shared neural resource supporting hierarchical processing across music and language and suggest a relevant marker of the relationship between rhythm processing and grammar abilities in elementary-school-age children, previously observed only behaviorally.

Keywords: EEG, language development, syntax, musical rhythm, dynamic attending.

Introduction

Recent studies have shown commonalities between musical rhythm and grammar. Children who demonstrate better rhythmic perception skills tend to show enhanced performance in syntactic tasks (Gordon, Shivers, et al., 2015; Nitin et al., 2023; Politimou et al., 2019; Swaminathan & Schellenberg, 2019; cf. Ozernov-Palchik et al., 2018), especially when complex syntactic structures are involved (Gordon, Jacobs, et al., 2015; Lee et al., 2020). Moreover, rhythmic structure affects the processing of grammatical structure in speech in adults (Kotz et al., 2009; Schmidt-Kassow & Kotz, 2008). Rhythmic priming paradigms have also shown that grammar performance is positively affected by brief exposure to metrically regular rhythmic musical primes (Canette et al., 2019; Chern et al., 2018; Ladányi et al., 2021; Przybylski et al., 2013). Such relations between rhythm and grammar have been explained as the result of shared cognitive processes that are recruited when hierarchical structures are processed in both language and music (Fitch, 2013; Fitch & Martins, 2014; Ladányi, Persici, et al., 2020). Both rhythm and grammar are organized in tree-like structures in which lower levels are incorporated into higher levels and elements are ordered according to specific rules (Fitch, 2017). In music, listeners generally utilize regularly timed basic units (whether accented or not) to extract the underlying pulse, or beat, which serves as an anchor “around which other [rhythmic] events are organized” (Iversen, Repp, & Patel, 2009:58). Beats, in turn, are perceptually grouped and organized into a hierarchical structure called ‘meter’ (Lerdahl & Jackendoff, 1983), which allows to interpret the music input as patterns of strong and weak beats. Language is also constituted of elements that are ordered following a hierarchical structure and specific rules (Lashley, 1951), with words combining to form phrases and smaller phrases combining and/or moving to form larger phrases. Thus, grammar perception and production also require perception and manipulation of stimuli that unfold serially but that are organized hierarchically.

The ability to perform these operations in rhythm may have an evolutionary basis. Animal studies have shown that perceptually extracting the beat is an ability shared by birds and mammals

(Kotz et al., 2018). The pervasive nature of music across cultures (Mehr et al., 2019; Ravignani et al., 2017; Savage et al., 2015) and the finding that engaging in rhythmic activities enhances prosocial behavior and social interaction and bonding (Cirelli et al., 2014; Lang et al., 2017; Pearce et al., 2015; Tarr et al., 2016) have led to the hypothesis that the ability to perceive and synchronize with rhythms may have evolved in humans to facilitate communication and foster group cohesion (Honing, 2018; Patel & Iversen, 2014; Savage et al., 2020). Developmentally, it has been proposed that rhythmic processing guides speech segmentation and comprehension and grammar learning in children (Beier & Ferreira, 2018; Dilley & McAuley, 2008; Kotz et al., 2018; Kotz & Schwartze, 2010, 2016). Research has shown that sensitivity to rhythmic cues in speech such as stress patterns is already present at birth (Mehler et al., 1988; Morgan et al., 1987). Processing of auditory beat and meter has been demonstrated in premature newborns with a mean gestational age of 33 weeks (Edalati et al., 2023). The ability to perceive these cues is thought to facilitate the segmentation of speech input (Morgan et al., 1987) and to provide infants with an efficient mechanism for processing language across the lifespan (Gordon, Jacobs, et al., 2015).

A recent quantitative meta-analysis (Heard & Lee, 2020) provided evidenced suggesting overlapping neural structures recruited in rhythm and grammar tasks, specifically in the brain areas involved in temporal hierarchy processing and potentially in predictive coding, or the act of generating predictions on what will occur (Friston, 2005). Such processes are likely implicated in rhythm and grammar processing: both domains entail the hierarchical organization of serial temporal input and the listener's active prediction of the next item to efficiently process upcoming events (Kuperberg & Jaeger, 2016; Persici et al., 2019; Vuust & Vitek, 2014). Moreover, research has shown that the ability to predict upcoming input is facilitated by rhythmic regularities (Andreou et al., 2011; Jones et al., 2002; Jones & Boltz, 1989; Large & Jones, 1999; Repp, 2005; Repp & Su, 2013). Crucially, both temporal hierarchy processing and predictive coding may be subserved by the neural tracking of rhythms (Arnal & Giraud, 2012; Fiveash et al., 2021; Ladányi, Persici, et al., 2020), a mechanism that we here term 'neural entrainment'.

Neural oscillations, produced by networks of neurons firing synchronously (Luo et al., 2006), are found to be entrained (i.e., synchronized) by the rhythms of higher-level structures such as meter (Fujioka et al., 2015) and syntactic phrases (Ding, Melloni, et al., 2017). This entrainment, which is already evident to beat and meter in 6- and 7-month-old infants (Cirelli et al., 2016; Flaten et al., 2022), is thought to be important for rhythm processing (Fujioka et al., 2015), but also for speech decoding, processing, and comprehension (Ahissar et al., 2001; Ding, Patel, et al., 2017; Ghitza, 2012; Luo & Poeppel, 2007), as well as for other processes including visual attention (see also Obleser & Kayser, 2019).

According to the Dynamic Attending Theory (DAT: Jones, 2019; Jones & Boltz, 1989; Large & Jones, 1999), auditory rhythms entrain attention rhythms, such that there are increases in attention at time points in the stimulus that are temporally regular and predictable (e.g., beats in music or stress in language). These attention rhythms may depend on the neural entrainment of multiple nested oscillations (Jones, 2019). Such nested entrainment has been observed in language processing. As shown by Ding, Melloni, Zhang, Tian, and Poeppel (2016), when English and Mandarin adult speakers hear a series of spoken sentences that contain elements that are presented at a fixed rate, peaks of spectral energy are produced at multiple levels: in correspondence to the word rate, to the phrasal unit rate, and to the sentence rate. This suggests that the brain not only responds to surface features of the acoustic waveform but also encodes syntactic units (see also Ding, Melloni, et al., 2017). These findings suggest commonalities in how the brain processes musical and linguistic structure.

If neural entrainment subserves both rhythmic and syntactic processing (Ladányi, Persici, et al., 2020), individual differences in neural activity during rhythmic listening should also correspond to individual differences in hierarchical processing in language. To investigate neural responses to hierarchically-organized auditory rhythms, Iversen, Repp, and Patel (2009) examined adult participants' processing of rhythmic structures of two tones and one rest varying in accent placement—and thus, perceived beat structure—while they underwent magnetoencephalography

(MEG). Experimental conditions in Iversen et al. (2009) included listening to two types of rhythmic sequences that varied in the location of intensity accents marking the beat (i.e., in whether the first or the second tone of the sequence were played louder), and two other conditions in which the participants were asked to imagine the same intensity accents. Both oscillatory responses in the beta and gamma frequency bands, and Event-Related Fields (ERF; the magnetic counterpart of event-related potentials; ERPs), were found to be enhanced at time points that corresponded to sounds that were heard (or imagined) as the beat, which suggests that brain responses are sensitive to beat interpretation.

Neural activity in the beta and gamma frequency appears also relevant for rhythmic processing in subsequent studies. Beta oscillations were found to be linked to beat anticipation and processing (Fujioka et al., 2009, 2012; Kasdan et al., 2020) and thought to index meter representation (Fujioka et al., 2015) and to reflect the coupling of brain activity originated in distant brain regions, such as the auditory and motor cortices (Bartolo et al., 2014). As beta activity rebounds prior to the next stimulus and peaks are found in correspondence to expected events (Fujioka et al., 2012), this frequency band is also believed to play a role in predictive processes (Arnal & Giraud, 2012; Leventhal et al., 2012), which are important for efficient rhythmic processing, given the periodicity and regularity of most rhythmic patterns (Kotz et al., 2018). Gamma band activity is also thought to be involved in rhythmic processing: peaks in evoked (phase-locked) gamma activity are found after the onset of expected tones, with power changes that are modulated in response to strong and weak beats (Zanto et al., 2005). Moreover, peaks in induced (non-phase-locked) gamma persist even when expected tones are omitted (Zanto et al., 2006). These findings have been interpreted as suggesting a role of gamma in the formation of temporal expectancies, in internal anticipatory timing, and thus in beat perception (Fujioka et al., 2009; Zanto et al., 2005; Zanto et al., 2006).

Both bands were also found to be implicated in grammar processing. Bastiaansen, Magyari, and Hagoort (2010) showed with MEG that a power increase in the beta frequency band occurs in

correspondence to the timing of unification operations, that is, the process of combining individual word information into the representation of the whole utterance in adults. These results are consistent with the idea that beta is also involved in the transmission of *content*-specific predictions (and thus, in predictive coding; Arnal & Giraud, 2012). Gamma has also been associated with language skills involving hierarchical processing in the study by Ding and colleagues (2016) mentioned above: the peaks in activity found at the syllable, phrasal, and sentential level suggest the existence of cortical networks supporting the concurrent encoding of multiple linguistic structures, including phrases and sentences.

Here we adapted Iversen et al. (2009)'s paradigm by presenting six-year-old children with rhythmic tone-tone-rest sequences differing in placement of an intensity accent marking the beat, while recording electroencephalography (EEG). The placement of an intensity accent either on the first or on the second tone of the sequence was expected to generate two distinct beat percepts. This expectation was based on prior results, using the same paradigm with typically-developed adults (Iversen et al., 2009) and adults with a neurodevelopmental disorder associated with atypical sensory processing and attentional difficulties called Williams syndrome (Kasdan et al., 2020), and on research showing that neural responses to the beat are already detectable in infancy (Cirelli et al., 2016; Winkler et al., 2009).

As mentioned above, beat perception entails processing of temporal information in a hierarchical fashion and is thus an example of hierarchical processing in the music domain. In line with previous studies (e.g., Iversen et al., 2009; Kasdan et al., 2020), we assumed that greater efficiency in capturing differences in temporal patterns would reflect better beat processing and encoding. The same children were administered standardized tests of rhythm discrimination abilities and grammar skills. The aim was to investigate whether enhanced tracking of hierarchical structures in rhythm resulted in better manipulation of hierarchical structures in language. More specifically, we aimed to examine whether individual differences in neural responses to the beat were associated with and predicted individual differences in grammar task performance over and

above behavioral rhythm discrimination performance (an effect previously shown in Gordon, Jacobs, et al., 2015; Gordon, Shivers, et al., 2015, as mentioned above). Children in this age range are an interesting population because they are still in the process of developing their grammar (Arndt & Schuele, 2013) and beat perception (Nave-Blodgett et al., 2021) abilities. Although they have reached peak cortical grey matter volume, they are still undergoing important changes in brain development (Bethlehem et al., 2022). Investigating how individual differences in one domain relate to individual differences in the other domain in this population is particularly important for our understanding of the mechanisms underlying language development.

Children's neural activity was recorded while they listened passively to the auditory stimuli. Given the associations found between rhythm and language in other work (e.g., Chern et al., 2018; Gordon, Shivers, et al., 2015; Nitin et al., 2023) and the hypothesized shared mechanism for hierarchical processing between the two domains (Heard & Lee, 2020; Ladányi, Persici, et al., 2020), we expected individual differences in the magnitude of neural responses to these rhythms to relate to individual differences in grammar task performance, based on the assumption that greater neural responses represent more effective encoding of the rhythms. Neural responses were quantified by looking at each individual child's neural differentiation of different accent patterns, in beta and gamma bands, in order to arrive at EEG-based metrics of their effectiveness of differentiating beat patterns. In particular, we explored whether these evoked beta and gamma EEG patterns could predict children's proficiency in two grammatical categories, Complex Syntax and Transformation over and above performance in a behavioral rhythm task.

The term 'Complex Syntax' refers to sentences that contain multiple clauses and thus have complex structural dependency relations (e.g., relative clauses: "the woman ate the fish *that her husband caught in the river*"). These utterances that include subordinate, infinite, complement, and relative clauses, are acquired between the ages of two and three years (Bloom et al., 1984). However, as opposed to simpler structures (Vasilyeva et al., 2008), growth in complex syntax continues throughout the school years (Arndt & Schuele, 2013). The term 'Transformation' (related

to the syntactic operation called Movement; Radford, 1988) refers to uni-clausal sentences with a non-canonical word order (e.g., wh-interrogatives in English: “what did the woman eat?”), requiring the reordering of sentence elements before responding. Thus, both Transformation and Complex Syntax require individuals to perform complex grammatical operations. However, these operations are of greater complexity in the case of Complex Syntax, which comprises multi-clausal sentences with longer structural dependencies than Transformation (Diessel, 2004). See Figure 1 for a visual depiction of these dependencies. The ability to perform such operations is fundamental for efficient language processing and development (Diessel, 2004). Rhythm discrimination abilities were tested in two tasks in which children were required to judge whether multiple successive presentations of a rhythm were the same or different. Note that these tasks tapping into children’s general rhythm perception abilities rely on sequence learning and memory-based skills (Fiveash et al., 2022) and may potentially tap into a separable rhythm sequence-based construct from the beat perception task assessed with EEG.

Prior behavioral studies with school-aged children have shown that rhythmic processing skills predict spoken grammar performance, both in general (Gordon, Shivers, et al., 2015) and in the two above-mentioned specific sub-categories (Gordon, Jacobs, et al., 2015; Lee et al., 2020). As discussed above, this link between rhythm perception and language production abilities may be due to shared biology via partially overlapping brain networks (Heard & Lee, 2020). According to recent theoretical accounts, behavioral (phenotypic) associations between musical and language traits may also partly result from genetic pleiotropy, or underlying common genetic architecture, among those traits (Fiveash et al., 2021; Ladányi, Persici, et al., 2020; Nayak et al., 2022). The possibility of uncovering overlapping underlying neurobiology across distinct skills/tasks is a particular motivation for the present work. Behaviorally, individual differences in hierarchical rhythmic ability may be associated with an advantage in spoken tasks. If hierarchical processing in both domains is subserved by neural entrainment, we hypothesize that individual differences in neural responses to musical rhythm (manifesting in peaks in beta and gamma at the onset of the

beat) will correspond to individual differences in grammar ability, especially in the case of sentences that require more refined grammatical operations, i.e., in Complex Syntax.

Figure 1

Syntactic trees of sentence examples of simple syntax, transformation, and complex syntax

Materials and Methods

Participants

This study reports EEG data of a cohort of participants for whom behavioral scores were previously reported (Gordon, Shivers, et al., 2015). Detailed participant characteristics and behavioral scores of the 25 children who participated (12 females, 13 males; 21 right-handed, 4 left-handed), ages between 5;11 and 7;1 years (mean: 6;6 years, $SD = 4$ months), are reported in Table 1. All were native speakers of American English and, as reported by their parents, had normal hearing, normal neurological health, and typical language, cognitive, and emotional development. Mean maternal education (used as proxy for socio-economic status (SES)) corresponded to three or four years of undergraduate education; children had little music experience, on average corresponding to a year of music class in school. Non-verbal intelligence was measured using the

Primary Test of Nonverbal Intelligence (PTONI; Ehrler & McGhee, 2008). See Table 1 for more information.

The study was approved by the Institutional Review Board of Vanderbilt University (Nashville, TN, United States of America), in agreement with the Declaration of Helsinki. Written informed consent and verbal assent were obtained from the parent and child respectively.

Table 1

Participants' characteristics and results of the behavioral tests as reported in Gordon, Shivers et al., 2015

	Mean (SD)	Percent correct (SD)
<i>N</i>	25	/
Age	6;6 (0;4)	/
Males: females	13:12	/
Maternal education level (9 levels)	7.32 (0.83)	/
Music experience (years)	1.08 (0.81)	/
Nonverbal intelligence (standard PTONI score)	110 (22.7)	/
SPELT-3 standard score	114 (6.87)	/
Transformation score (11 items)	9.52 (1.55)	86.54 (14.16)
Complex Syntax score (12 items)	9.6 (1.61)	81.33 (13.45)
BBA behavioral rhythm test (d'prime)	1.10 (0.76)	/
PMMA behavioral rhythm test	/	70.9 (12.6)

Behavioral Assessments

Expressive Grammar Skills

Grammar ability was tested with the Structured Photographic Expressive Language Test (SPELT-3; Dawson et al., 2003), in which children are presented with various photographs and asked questions designed to elicit specific syntactic constructions such as relative or interrogative

clauses. Appropriate responses require both efficient comprehension of the verbal probe delivered by the experimenter and developed expressive abilities. Standard (age-normed) total scores and grammatical category mean scores for Complex Syntax and Transformation items are reported in Gordon, Jacobs et al. (2015) and in Table 1. Standard (age-normed) total scores showed a performance within the normal range for all participants (mean: 114.16; $SD = 6.87$, range: 98-125, indicating typical development).

Musical Rhythm Skills

Rhythm discrimination abilities were tested with two computer-based games: the children's beat-based advantage assessment (BBA; originally adapted from adult work on beat perception by Grahn & Brett, 2009), and the rhythm section of the Primary Measures of Music Audiation (PMMA; Gordon, 1979). In both tests children were asked to judge whether multiple successive rhythm presentations were the same or different. BBA includes 28 test trials, including both simple and complex rhythms; PMMA includes 40 test trials. Both tasks were used because of their unique attributes: only PMMA is a standardized test of music aptitude; on the other hand, BBA addresses beat perception specifically (e.g., Fiveash et al., 2022, Grahn and Brett, 2009, and Niarchou et al., 2021, for previous papers using this task), whereas PMMA includes stimuli with more varied metrical structures (see Gordon, Shivers, et al., 2015 for more details on the two tasks). A behavioral Rhythm Composite score was calculated by averaging z-transformed d' scores on the BBA assessment (commonly used in signal detection studies; Macmillan & Creelman, 2005) and z-transformed PMMA percent correct scores (note that the BBA and PMMA z-transformed scores were moderately and significantly correlated ($r = .43, p = .030$) and that this new variable was highly correlated with the previously reported Rhythm Composite measure, which was obtained by averaging percent correct scores from the two tests; $r = .99, p < .001$). See Gordon, Shivers, et al. (2015) for more details.

Electroencephalography

Stimuli. The auditory sequences in the EEG paradigm were adapted from the physical accent conditions used in Iversen, Repp, and Patel (2009); see Figure 2. In this study we did not include the imagined beat conditions (for which top-down control is important) used in Iversen et al.'s study for theoretical and practical purposes. Most importantly, we expected each of physical accent condition patterns to elicit different beat percepts (i.e., perception of patterns with different beat positions). This would be the case if children's early latency neural responses to rhythms are affected by physical stimuli, a phenomenon that has been previously shown using the same paradigm with typically developed adults (Iversen et al., 2009) and with adults with Williams syndrome (Kasdan et al., 2020). We thus predicted that fluctuations in early ERP sensory responses and in beta and gamma evoked activity would reflect differentiation between the two rhythmic sequences. Second, a shorter experiment with only implicit listening allowed keeping the session at a duration that reduced variance in children's ability to follow task demands. In each of the two physical accent conditions, tones had a frequency of 1000 Hz, a duration of 50 ms, an intensity of 58 dB, and an inter-onset interval of 200 ms between the first and second tone in each pair (the tone-tone-rest pattern thus had a duration of 600 ms). In the Accent1 condition, sequences had a strong-weak-rest pattern: the accent, conveyed by increasing the intensity of the sound by 10 dB, occurred on the first tone; in the Accent2 condition, the accent occurred on the second tone, thus creating a weak-strong-rest pattern (see Figure 2). Each block consisted of 50 repetitions of the same pattern for a duration of 30 seconds and was presented nine times per condition in random order (for an overall task duration of nine minutes). In the analyses, we excluded the first two trials in each block and analyzed only the following forty-eight repetitions, for a total of 864 trials for analysis.

Figure 2

Stimulus conditions in the EEG paradigm (used with permission from Kasdan et al., 2020)

Procedure

EEG Acquisition

Participants' EEG recordings were collected individually in a sound-dampened room at the EEG Lab at the Vanderbilt Kennedy Center in Nashville, Tennessee (USA). Brain activity was recorded continuously using 128 Ag/AgCl electrodes embedded in soft sponges (EGI Geodesic Sensor Net, Eugene, OR, USA). Lower eye channels were only available on some sizes of the EEG nets and consequently were excluded from further analyses. EEG signals were sampled at 500 Hz for temporal precision (the data of two participants were inadvertently sampled at 250 Hz and then later upsampled to 500 Hz). Data was acquired in Net Station 4.4 with high-impedance amplifier NetAmps 200 and with a Butterworth hardware filter of 0.1 to 200 Hz; impedances were adjusted to below 40 k Ω before the start of the paradigm. Stimuli were presented at 72 dB through a single speaker placed above the participant's head. EEG was recorded while participants listened passively to the auditory stimuli; no behavioral responses were required. To keep participants engaged but still during data acquisition, an age-appropriate video with muted sound was shown. Participants were asked to watch the video and stay still and that they would "hear some sounds"; no further instructions were given. The entire session lasted about 45 minutes and included an additional experiment for a separate project.

EEG Data Preprocessing

Data processing was performed using the EEGLAB toolbox (Delorme & Makeig, 2004) in MATLAB R2017b (The Mathworks Inc., 2017). Signals were smoothed using a 100-Hz low-pass filter and a 0.5-Hz high-pass filter to eliminate non-brain-related frequencies. Line noise was cleaned using the `pop_cleanline` function. Bad electrodes characterized by consistently high noise levels were identified using the Artifact Subspace Reconstruction (ASR) approach and interpolated using the spherical spline interpolation algorithm (Perrin et al., 1989). Data were re-referenced to the average of all channels.

Artifacts in the data were identified using Independent Component Analysis (ICA); the type of artifact was identified with the help of ICLabel (Pion-Tonachini et al., 2019). Cardiac and ocular artifacts were manually removed (range: 0-3 components (heart, eye blink or sideways eye movement) per participant; mean = 1.48). Next, data were divided into 1600-ms epochs with the interval of [-400, +1200], time-locked to the onset of the first tone (tone-tone-rest, in both conditions); a wide window is needed for time-frequency analyses to avoid window-edge artifacts (Roach & Mathalon, 2008). Epochs were rejected if they exceeded a -100/+100 μ V threshold, as in Kasdan et al. (2020). An average of 7.38% ($SD = 10.25\%$) of epochs were rejected. A technical error caused a subset of $n = 13$ participants to have received an extra two blocks of trials during data acquisition; these were retained during data clean-up to improve ICA reliability (Debener et al., 2010) and then discarded in the following way. First, we computed the number of epochs kept after cleaning of the $n = 12$ that received the correct number of trials and found that it was 407 trials for Accent1 and 406 trials for Accent2. To prevent the other $n = 13$ subset of data from having a disproportionate impact on the signal-to-noise ratio, we removed the last 75 clean epochs from 12 of those 13 participants for further analysis (the remaining 13th participant had only 291 and 220 trials remaining after artifact rejection respectively and thus no further trials were removed). In the final dataset of $N = 25$, the mean number of epochs was not different between conditions ($t(24) = 0.605, p = .551, SD = 19.84$; for Accent1: mean trials = 409 ($SD = 33$) and Accent2: mean trials =

407 ($SD = 46$). Note that analysis including extra epochs, for the purpose of comparison, did not significantly affect any of the final results; p-values and cluster latencies were virtually identical (see Table 4S in the Supplementary materials).

Data Analysis

Similar to prior work using this paradigm (Iversen et al., 2009; Kasdan et al., 2020), we conducted ERP and time-frequency analysis on the EEG data using the FieldTrip Toolbox (Oostenveld et al., 2011). Statistical analyses on brain-behavior relationships were carried out using R (R Core Team, 2022).

Event-related Potentials (ERPs). Event-related potential (ERPs) were generated from the average across trials for each condition and utilized for evoked time-frequency analyses (see below). ERPs were then trimmed to [-100 to 700ms], baseline-corrected with a baseline of [-100, 0] ms and low-pass filtered with a Butterworth filter of 30 Hz for subsequent ERP analyses. Line noise was further removed with the DFT filter.

Time-frequency Representations (TFRs). Evoked (phase-locked) activity for each condition was obtained by convolving the average ERP waveform with a family of Morlet wavelets with a width of six cycles, from 12 Hz to 50 Hz, with a frequency step of 1 Hz and a time step of 2 ms in the time window [-200, +800], with zero being the onset of each tone-tone-rest pattern (see Tallon-Baudry et al., 1996, and Herrmann et al., 2005, for more details on this analysis). Note that this wide window was only used for TFR calculation; overlapping latencies were not tested statistically (see below). Power values for the resulting time frequency representations (TFRs) were then normalized (baseline-corrected) at each time point, frequency, and channel as relative power change in relation to the mean total power averaged across time points and across both conditions separately for each frequency and channel, to compensate for inter-individual variability in absolute power.

Cluster-based Permutation Statistical Analyses. Statistical analyses were conducted in FieldTrip, using a cluster randomization procedure to identify consistent trends in activity in clusters of channels and using cluster-based permutation tests coded for within-subjects design to test for differences in activity between conditions (Maris & Oostenveld, 2007). For ERPs, the Accent1 vs. Accent2 conditions were compared in the time window [-100, +500] (to avoid testing overlapping latencies) at each time point and channel using a dependent-samples t-test. All the data points from adjacent channels with significant t-values at $p < .025$ (two-tailed) were used to generate clusters; all the other data points were zeroed. Adjacency was determined via the distance between neighboring channels using the FieldTrip triangulation parameter, and a minimum of two neighboring channels at a given time point and channel were required for that data point to be included in a cluster (i.e., three channels were the minimum to meet the adjacency criteria). The cluster-level test statistic for each cluster was then calculated by summing all the t -values within that cluster. The significance of each cluster was assessed using a Monte Carlo method: randomly permuted values from both conditions were taken and pooled together to form two new subsets (simulated dummy conditions), which were used to obtain a dummy cluster test statistic. The same process was repeated 5,000 times, to obtain 5,000 dummy clusters. The resulting cluster p -values are the proportions of permutations in which the true cluster statistic exceeds the simulated cluster (dummy) statistic. Clusters with a cluster $p < .05$ were considered statistically significant. The same procedure was used for time-frequency representations (TFRs) of Accent1 vs. Accent2, for average power within two frequency bands: 13-23 Hz for beta, 24-50 Hz for gamma.

Individual Differences and Brain-behavior Correlations. Variables representing the difference of neural activity between conditions were obtained for TFRs in each frequency band, using a method previously reported by Lense et al. (2014): power values (for time-frequency data) of the difference between conditions at each time point and channel in the latency band (for clusters that surpassed group-level statistical significance) are summed for each participant. In other words, the group-level cluster parameters for the spatial and temporal distribution of the cluster were

applied to the individual data at each participant and the sum of the difference of values at each time and point and condition are computed. Thus, for each participant this procedure resulted in a single value for each of the four cluster-sums (i.e., for the beta and gamma clusters for the Beat1 and Beat2 effects).

To determine if neural responses to rhythm were associated with individual differences in spoken grammar skill, we performed Spearman correlations between significant beta and gamma evoked clusters and the total SPELT-3 score or the scores in each of the two SPELT-3 subcategories of interest (all z-scored), controlling for age, non-verbal intelligence, music experience, and maternal education (as a proxy for SES) and with p-values adjusted for multiple comparisons (Benjamini-Hochberg correction). Note that the Beat1 effect clusters correspond to increased neural responses around the onset of the first tone (for Accent1 versus Accent2), and the Beat2 effect clusters correspond to larger neural responses around the onset of the second tone (for Accent2 versus Accent1). We focused on beta and gamma TFRs in relation to language task performance, given prior literature on the role of beta and gamma in rhythmic attending (see Introduction). The correlations between activity to the first vs. second tone and in beta vs. gamma are reported in the Supplementary materials.

Hierarchical regressions were then used to assess the potential contribution of neural markers of beat processing to grammar over and above the variance explained by behavioral musical rhythm (which was previously reported in Gordon et al., 2015a; 2015b). Models were compared using *F*-tests (Field, Miles, & Field, 2012). The variance explained by each model was examined by looking at Adjusted R^2 values. The analysis of individual differences in ERP amplitude (calculated following the same procedure as for TFRs) and of their relationship with syntactic scores was carried out as exploratory work and is reported in the Supplementary materials.

Results

Cluster-based Analysis of ERPs

Results of cluster-based permutation tests revealed two significant clusters in correspondence to Accent1 vs. Accent2 at the onset of the first tone (“Beat1 effect”; see Figure 3) and three significant clusters in correspondence to Accent2 versus Accent1 at the onset of the second tone (“Beat2 effect”; see Figure 3). Detailed ERP cluster results are reported in Table 2. Specifically, we found a negative ERP deflection in the neural activity over frontal regions of the scalp when the accent was on the first tone (ERP-Beat1effect-early-negativity-frontal: from -46 to 54 ms, cluster $p = .009$; Figure 3A), and a posterior positive effect around the same time window (ERP-Beat1effect-early-positivity-posterior; from -30 to 50 ms, cluster $p = .024$; Figure 3B). Given that the clusters occur at the same latencies and display nearly identical waveforms with opposite polarities, they might be two extremes of the same dipole. We also found three significant clusters showing a Beat2 effect: a frontal negative effect (ERP-Beat2effect-late-negativity-frontal1 from 222 to 462 ms, cluster $p < .001$; Figure 3C), a posterior positive effect (ERP-Beat2effect-late-positivity-posterior from 214 and 410 ms, $p < .001$; Figure 3D), and, finally, a negative frontal effect (ERP-Beat2effect-late-negativity-frontal2) in the time window between 424 and 500 ms, cluster $p = .032$ (Figure 3E). Following the same reasoning stated above, we interpret the first two Beat2 effect clusters as the two extremes of the same dipole, and thus likely reflecting the same cortical source. The similar topographies of the two frontal Beat2 effect clusters also suggest that they might be the same brain source. Taken together, the early latencies of four out of five of the ERP clusters (with respect to beat onset) suggest that early sensory responses are modulated by beat perception.

Table 2

Characteristics of the significant clusters identified by cluster-based permutation tests of Event-Related Potentials (ERP)

Cluster label	Latency	Scalp distribution	Cluster p-value
ERP-Beat1effect-early-negativity-frontal	-46 to 54 ms	Frontal	.009
ERP-Beat1effect-early-positivity-posterior	-30 to 50 ms	Posterior	.024

ERP-Beat2effect-late-negativity-frontal1	222 to 462 ms	Frontal	< .001
ERP-Beat2effect-late-positivity-posterior	214 to 410 ms	Posterior	< .001
ERP-Beat2effect-late-negativity-frontal2	424 to 500 ms	Frontal	.032

Figure 3

Grand average ERP (N = 25) Beat 1 (A, B) and Beat 2 (C, D, E) effects. The dotted lines indicate the start and end latencies of the significant clusters found in correspondence to the first beat (Beat1 effect; onset of the sequence at 0 ms) or in correspondence to the second beat (Beat2 effect; onset of the sequence at 0 ms). ERPs for condition Accent1 (strong-weak-rest) are denoted in blue, and ERPs for condition Accent2 (weak-strong-rest) are in red. ERP plots (on the left of each panel) show amplitude in microvolts averaged over all the channels belonging to the significant cluster (y-axis) with negative up by convention, and time in ms (x-axis). Topographic plots (on the right) show scalp distribution of amplitude at time points indicated, which were chosen to correspond to peaks within the cluster window. Channels belonging to the significant cluster are indicated with asterisks. Panel A shows the ERP-Beat1effect-early-negativity-frontal cluster over fronto-central regions (cluster $p = .009$). Panel B shows ERP-Beat2effect-early-positivity-posterior cluster over posterior central regions (cluster $p = .024$). Panel C shows the ERP-Beat2effect-late-negativity-frontal1 cluster over fronto-central regions (cluster $p < .001$). Panel D shows the ERP-Beat2effect-late-positivity-posterior cluster over posterior central regions (cluster $p < .001$). Panel E shows the ERP-Beat2effect-late-negativity-frontal2 cluster over fronto-central regions (cluster $p = .032$)

Cluster-based Analysis of TFRs

Results of cluster-based permutation tests revealed significant evoked beta and gamma activity in correspondence to the beat onset in each condition, which was greater for the accented beat. Specifically, significantly greater neural activity in beta band with a widespread scalp distribution (EEG-beta-Beat1effect cluster $p < .001$; Figure 4A) and in gamma band with a posterior-central distribution (EEG-gamma-Beat1effect cluster $p = .033$; Figure 4B) were found in correspondence to the first tone of the Accent1 versus Accent2 condition (Beat1 effect). Similarly, greater activity in the beta band (cluster $p = .006$; Figure 5A) and in gamma band (cluster $p = .028$; Figure 5B), with both clusters distributed over fronto-central regions, were found in correspondence to the second tone in the Accent2 condition versus Accent1 condition (Beat2 effect; see Figure 5). Cluster latencies are reported in Table 3.

Table 3

Characteristics of the significant clusters identified by cluster-based permutation tests of beta and gamma evoked activity during the EEG rhythm task, and their significant associations with individual differences in language skills

Cluster label	Latency	Scalp distribution	Cluster p-value	Significant association with language skills		
				Grammar		
				category	$r_{(s)}$	p
EEG-beta-Beat1 effect	-92 to 146ms	Widely distributed	< .001	SPELT-3 total	.60	.018
				Transformation	.56	.030
				Complex Syntax	.63	.014
EEG-beta-Beat2 effect	214 to 352ms	Fronto-central	.006	-		
EEG-gamma-Beat1 effect	50 to 120ms	Posterior-central	.033	Complex Syntax	.62	.014
EEG-gamma-Beat2 effect	238 to 306ms	Fronto-central	.028			

Note. P-values were adjusted for multiple comparisons using the Benjamini-Hochberg correction.

Figure 4

Beat 1 effect. Time-frequency representations (TFRs) and topographies for grand average ($N = 25$), showing normalized power changes in EEG evoked beta (panel A) and gamma (panel B) neural activity relative to the first tone (Beat1 effect). TFRs are shown on the left side of each panel and are the average of all the channels belonging to the cluster; the black dashed box indicates the time and frequency boundaries of the significant clusters. Representative topographies (on the right side of each panel) are shown at the indicated latencies within the clusters. Color scale represents the percent change from baseline (i.e., normalized power). Significant channels are marked with black asterisks. As signaled by the darker red colors, increased beta and gamma neural activity is found at the first beat when this was accented (in the Accent1 condition (top row) as compared to the Accent2 condition (bottom row))

Figure 4. Beat 1 effect: Grand average Evoked EEG beta and gamma clusters

Figure 5

Beat 2 effect. TFRs and topographies for EEG evoked beta (panel A) and gamma (panel B) neural activity relative to the second tone (Beat2 effect). See Figure 3 for description of representation. Increased beta and gamma neural activity is found for the second beat when this was accented (in the Accent2 condition (bottom row) as compared to the Accent1 condition (top row))

Figure 5. Beat 2 effect: Grand average Evoked EEG beta and gamma clusters

Brain-behavior Relationships

Neural Markers of Beat Processing and Expressive Language Ability: Correlations

The analysis of beta and gamma activity yielded significant associations with language scores, as reported on Table 3 and as shown in Figure 6. For the beta band, the results showed strong and significant correlations between the EEG-beta-Beat1effect cluster and SPELT-3 total (Figure 6A), and also with both the Transformation (Figure 6B) and Complex Syntax (Figure 6C) sub-scores.

In the gamma band, a strong and significant correlation was also found between the EEG-gamma-Beat1effect cluster and Complex Syntax (Figure 6D). No significant correlations were found between the EEG-beta-Beat2effect cluster and SPELT-3 (whether total or in each subcategory; SPELT-3 total: $p = .838$; Transformation: $p = .838$; Complex Syntax: $p = .759$), between the EEG-gamma-Beat1effect cluster and SPELT-3 total ($p = .107$) or Transformation ($p = .195$), or between the EEG-gamma-Beat2effect cluster and any of the SPELT-3 categories (SPELT-3 total: $p = .107$; Transformation: $p = .303$) or Complex Syntax ($p = .324$).

To summarize, a larger Beat1 effect (suggesting enhanced neural responses to the first tone when it was accented) was positively associated with language scores, whereas a larger Beat2 effect (suggesting enhanced neural responses to the second tone when it was accented) was not significantly associated with language scores, contrary to our hypothesis.

Figure 6

Statistically significant partial correlations between Z-transformed expressive grammar scores on the SPELT-3 and evoked variables, controlling for age, nonverbal IQ, music experience, and maternal education. All partial correlations are graphed as the correlation between the residuals of two linear regression models with the covariates as predictors and the expressive grammar score or evoked cluster of interest as dependent variable. Panels A, B, and C show the significant partial correlations between the EEG-beta-Beat1effect and SPELT-3, Transformation, and Complex

*Syntax, respectively. Panel D shows the significant partial correlation between EEG-gamma-Beat1 effect and Complex Syntax. Note that the Beat1 effect corresponds to larger responses near the onset of the first tone in Accent1. Thus, higher, positive numbers indicate larger neural activity. See Methods and Results for more detail. * $p < .05$, ** $p < .01$, *** $p < .001$*

Hierarchical Regressions

As reported in Gordon, Jacobs, et al. (2015), and Gordon, Shivers, et al. (2015), the Rhythm Composite score (calculated here as the mean of the z-scored BBA d' and PMMA percent correct) explained unique variance in SPILT-3 scores, whether total or within the Transformation and Complex Syntax subcategories. Here, we added the significant beta and gamma evoked clusters to see if additional variance in the grammar scores of our participants could be explained by their neural responses to rhythm over and above that explained by rhythm behavior.

Table 4 shows the full results of these analyses¹. Adding the EEG-beta-Beat1effect cluster to the base model (i.e., Model 1, which included age, non-verbal intelligence, music experience, maternal education, and the behavioral rhythm score as predictors) increased significantly the ability of the model to fit the data ($F(1, 18) = 18.373, p < .001$; see Table 4 for AIC and BIC values). The more complex model (i.e., Model 2) explained 26.6% more variance in the total SPELT-3 score than Model 1 (the Adjusted R^2 value changed from 0.442 in Model 1 to 0.708 in Model 2). Although the EEG-beta-Beat1effect cluster ($\beta = .512$) had less impact on the total SPELT-3 scores than the Rhythm Composite score ($\beta = .615$) in Model 2, its addition still contributed to significantly increase the amount of variance explained in the grammatical scores. Adding the EEG-gamma-Beat1effect cluster to the base model also improved significantly model fit ($F(1, 18) = 11.021, p = .004$). The variance explained in the total SPELT-3 scores this time was larger by 19.3% (the Adjusted R^2 value changed from 0.442 in Model 1 to 0.635 in Model 4). Again, in the final model, the Rhythm Composite score was the most influential predictor ($\beta = .566$; β of the EEG-gamma-Beat1effect cluster = .468). On the contrary, the EEG-beta-Beat2effect and EEG-gamma-Beat2effect clusters did not significantly contribute to explain unique variance in these scores (beta: $p = .409$, gamma: $p = .376$). See Figure 7 to see the standardized beta coefficients and their 95% confidence intervals in these models.

Similar results were found for the Complex Syntax scores as for total SPELT-3 scores. Complex Syntax results showed significant ($p = .001$) and unique variance (28.3%; the Adjusted R^2 value changed from 0.308 in Model 1 to 0.591 in Model 2) explained by the EEG-beta-Beat1effect cluster ($F(1, 18) = 14.118, p = .001$). In this model, the added neural variable was also the most influential ($\beta = .532$; Rhythm Composite score $\beta = .231$). Adding the EEG-gamma-Beat1effect

¹ Note that running these analyses using the scores obtained in the validated, standardized rhythm discrimination test (i.e., PMMA) as predictor, rather than Rhythm Composite scores, does not significantly affect the results relative to the effects of the evoked clusters.

cluster to the base model also increased significantly ($F(1, 18) = 14.846, p = .001$) the proportion of variance explained, this time by 29.2% (Adjusted R^2 value change from 0.308 in Model 1 to 0.600 in Model 4). Again, the added neural variable was the most influential predictor of the children's Complex Syntax scores ($\beta = .569$; Rhythm Composite score $\beta = .164$). No significant results were found when adding the EEG-beta-Beat2effect ($p = .243$) or EEG-gamma-Beat2effect ($p = .533$) clusters.

For the Transformation scores, results showed that the EEG-beta-Beat1effect cluster explained significant ($p = .007$) and 19% unique variance (the R^2 value changed from 0.380 in Model 1 to 0.570 in Model 2; $F(1, 18) = 9.419, p = .007$). The effect of the EEG-beta-Beat1effect cluster ($\beta = .445$) on the Transformation scores was stronger than that of the Rhythm Composite score ($\beta = .380$). However, none of the other evoked variables significantly contributed to explain unique variance in these scores (the EEG-beta-Beat2effect: $p = .189$; EEG-gamma-Beat1effect: $p = .094$; EEG-gamma-Beat2effect: $p = .821$).

Table 4

Hierarchical regressions model fit and summary

Dependent Variable	Model	Model Fit						Predictor	Standardized beta	S.E.	t-value	p-value
		<i>F</i>	<i>df</i>	<i>p</i>	Adjusted R^2	AIC	BIC					
SPELT-3 total score	Model 1 (base model)	4.799	5, 19	0.005	0.442	63.509	72.041	Intercept	0.000	0.149	0.000	1.000
								Age	0.071	0.168	0.423	0.677
								Nonverbal IQ	0.063	0.165	0.382	0.707
								Music Experience	0.091	0.158	0.575	0.572
								Maternal Education (SES)	0.121	0.158	0.763	0.455

							Rhythm	0.658	0.180	3.664	0.002
							Composite				
							Score				
Model	10.719	6,	<	0.708	47.923	57.674	Intercept	0.000	0.108	0.000	1.000
2		18	.001				Age	0.138	0.122	1.129	0.274
							Nonverbal	0.194	0.123	1.573	0.133
							IQ				
							Music	0.196	0.117	1.670	0.112
							Experience				
							Maternal	0.052	0.115	0.451	0.657
							Education				
							(SES)				
							Rhythm	0.615	0.130	4.723	<.001
							Composite				
							Score				
							EEG-beta-	0.512	0.119	4.286	<.001
							Beat1effect				
Model	4.059	6,	0.010	0.433	64.535	74.286	Intercept	0.000	0.151	0.000	1.000
3		18					Age	0.068	0.169	0.400	0.694
							Nonverbal	0.072	0.167	0.432	0.671
							IQ				
							Music	0.117	0.163	0.721	0.480
							Experience				
							Maternal	0.135	0.160	0.840	0.412
							Education				
							(SES)				
							Rhythm	0.709	0.191	3.718	0.002
							Composite				
							Score				
							EEG-beta-	0.146	0.173	0.846	0.409
							Beat2effect				
Model	7.946	6,	<	0.635	53.568	63.319	Intercept	0.000	0.121	0.000	1.000
4		18	.001				Age	0.156	0.138	1.131	0.273
							Nonverbal	0.046	0.134	0.343	0.736
							IQ				
							Music	0.231	0.135	1.710	0.104
							Experience				

								Maternal	-0.026	0.135	-	0.848
								Education			0.194	
								(SES)				
								Rhythm	0.566	0.148	3.827	0.001
								Composite				
								Score				
								EEG-	0.468	0.141	3.320	0.004
								gamma-				
								Beat1effect				
Model	4.099	6,	0.009	0.437	64.391	74.142	Intercept	0.000		0.150	0.000	1.000
5		18					Age	0.051		0.170	0.299	0.768
								Nonverbal	0.059	0.166	0.357	0.725
								IQ				
								Music	0.108	0.160	0.672	0.510
								Experience				
								Maternal	0.146	0.161	0.904	0.378
								Education				
								(SES)				
								Rhythm	0.574	0.203	2.827	0.011
								Composite				
								Score				
								EEG-	-0.169	0.186	-	0.376
								gamma-			0.907	
								Beat2effect				
Transformation	Model	3.940	5,	0.013	0.380	66.140	74.672	Intercept	0.000	0.157	0.000	1.000
score	1 (base		19					Age	0.443	0.177	2.509	0.021
								Nonverbal	-0.242	0.174	-	0.180
								IQ			1.391	
								Music	0.116	0.167	0.692	0.497
								Experience				
								Maternal	0.132	0.167	0.794	0.437
								Education				
								(SES)				
								Rhythm	0.417	0.189	2.204	0.040
								Composite				
								Score				
Model	6.308	6,	0.001	0.570	57.619	67.370	Intercept	0.000		0.131	0.000	1.000
2		18					Age	0.501		0.148	3.382	0.003

							Nonverbal	-0.128	0.149	-	0.402
							IQ			0.859	
							Music	0.206	0.142	1.451	0.164
							Experience				
							Maternal	0.073	0.140	0.519	0.610
							Education				
							(SES)				
							Rhythm	0.380	0.158	2.403	0.027
							Composite				
							Score				
							EEG-beta-	0.445	0.145	3.069	0.007
							Beat1effect				
Model	3.744	6,	0.014	0.407	65.675	74.426	Intercept	0.000	0.154	0.000	1.000
3		18					Age	0.438	0.173	2.534	0.021
							Nonverbal	-0.227	0.170	-	0.200
							IQ			1.332	
							Music	0.159	0.166	0.955	0.352
							Experience				
							Maternal	0.155	0.164	0.948	0.356
							Education				
							(SES)				
							Rhythm	0.502	0.195	2.570	0.019
							Composite				
							Score				
							EEG-beta-	0.241	0.177	1.366	0.189
							Beat2effect				
Model	4.173	6,	0.008	0.442	64.133	73.884	Intercept	0.000	0.149	0.000	1.000
4		18					Age	0.499	0.170	2.929	0.009
							Nonverbal	-0.253	0.165	-	0.142
							IQ			1.534	
							Music	0.207	0.167	1.245	0.229
							Experience				
							Maternal	0.036	0.167	0.213	0.834
							Education				
							(SES)				
							Rhythm	0.357	0.183	1.952	0.067
							Composite				
							Score				

								EEG-	0.308	0.174	1.769	0.094
								gamma-				
								Beat1effect				
Model	3.129	6,	0.028	0.347	68.067	77.818	Intercept	0.000	0.162	0.000	1.000	
5		18										
								Age	0.438	0.183	2.395	0.028
								Nonverbal	-0.243	0.179	-	0.190
								IQ	1.361			
								Music	0.120	0.172	0.696	0.495
								Experience				
								Maternal	0.139	0.174	0.802	0.433
								Education				
								(SES)				
								Rhythm	0.394	0.219	1.805	0.088
								Composite				
								Score				
								EEG-	-0.046	0.201	-	0.821
								gamma-	0.230			
								Beat2effect				
Complex	Model	3.135	5,	0.031	0.308	68.887	77.419	Intercept	0.000	0.166	0.000	1.000
Syntax score	1 (base		19									
	model)											
								Age	0.311	0.187	1.669	0.111
								Nonverbal	0.173	0.184	0.944	0.357
								IQ				
								Music	0.261	0.176	1.482	0.155
								Experience				
								Maternal	0.257	0.176	1.459	0.161
								Education				
								(SES)				
								Rhythm	0.276	0.200	1.378	0.184
								Composite				
								Score				
Model	6.769	6,	.001	0.591	56.411	66.162	Intercept	0.000	0.128	0.000	1.000	
2		18										
								Age	0.381	0.145	2.633	0.017
								Nonverbal	0.309	0.146	2.119	0.048
								IQ				
								Music	0.370	0.139	2.666	0.016
								Experience				

							Maternal Education (SES)	0.186	0.137	1.358	0.191
							Rhythm Composite Score	0.231	0.154	1.495	0.152
							EEG-beta-Beat1effect	0.532	0.142	3.757	0.001
Model	2.919	6,	0.036	0.324	68.937	78.688	Intercept	0.000	0.164	0.000	1.000
3		18					Age	0.306	0.184	1.661	0.114
							Nonverbal IQ	0.187	0.182	1.030	0.317
							Music Experience	0.302	0.178	1.702	0.106
							Maternal Education (SES)	0.279	0.175	1.593	0.129
							Rhythm Composite Score	0.355	0.208	1.705	0.105
							EEG-beta-Beat2effect	0.228	0.188	1.209	0.242
Model	6.990	6,	.001	0.600	55.851	65.602	Intercept	0.000	0.127	0.000	1.000
4		18					Age	0.415	0.144	2.873	0.010
							Nonverbal IQ	0.153	0.140	1.091	0.290
							Music Experience	0.431	0.141	3.052	0.007
							Maternal Education (SES)	0.079	0.142	0.554	0.586
							Rhythm Composite Score	0.164	0.155	1.059	0.304
							EEG-gamma-Beat1effect	0.569	0.148	3.853	0.001
	2.598		0.054	0.285	70.332	80.083	Intercept	0.000	0.169	0.000	1.000

Model 5	6, 18	Age	0.296	0.191	1.546	0.139
		Nonverbal IQ	0.170	0.187	0.913	0.374
		Music Experience	0.275	0.180	1.521	0.146
		Maternal Education (SES)	0.277	0.182	1.525	0.145
		Rhythm Composite Score	0.209	0.229	0.914	0.373
		EEG-beta-Beat1effect	-0.133	0.210	-	0.533
		EEG-gamma-Beat1effect			0.636	
		EEG-gamma-Beat2effect				

Note. Significant effects are in bold. Adjusted R^2 indicates the proportion of variance explained adjusted for the number of predictors in the model. AIC = Akaike Information Criterion. BIC = Bayesian Information Criterion.

Figure 7

Standardized beta coefficients and 95% confidence intervals from the models on SPELT-3 scores. Model 1 includes age, nonverbal IQ, music experience, maternal education (SES), and the behavioral Rhythm Composite score as predictors. Models 2 and 4 additionally include the EEG-beta-Beat1effect and EEG-gamma-Beat1effect clusters, respectively.

Discussion

The aim of the present study was to identify neural oscillatory markers of beat processing that may relate to individual differences in language performance in children. We hypothesized that the strength of neural responses to the beat would be linked to individual differences in language skills, especially in hierarchical processing, based on previous behavioral findings indicating that musical rhythm discrimination skills predict expressive and receptive grammar performance (Gordon, Jacobs, et al., 2015; Gordon, Shivers, et al., 2015; Swaminathan & Schellenberg, 2019). Neural responses to the beat point to processes of neural entrainment, which are crucial for hierarchical processing in both rhythm and language (Ahissar et al., 2001; Ding, Patel, et al., 2017; Ghitza, 2012; Ladányi, Persici, et al., 2020; Luo & Poeppel, 2007); moreover, individual differences in neural entrainment may bootstrap acquisition of hierarchically organized structure during language development. Infants and newborns can process and neurally track rhythmic regularities in musical stimuli (Cirelli et al., 2016; Flaten et al., 2022) as well as in speech (Kalashnikova et al., 2019). Optimal entrainment, both internally between multiple oscillators (Jones, 2019) and to rhythm in music and grammatical structure in language, may help scaffold

hierarchical processing by facilitating temporal integration of smaller units into larger linguistic structures (Ding et al., 2016). Neural mechanisms of entrainment may thus account for a relative strength in a given child's ability to process hierarchical structures in music (Large & Jones, 1999) and to handle complex sentence structures during language acquisition.

Our study showed that the neural responses of six-year-old children peaked in correspondence to rhythmic auditory stimuli, converging with previous research findings in adults showing modulations of evoked beta, gamma, and ERF neural responses to different physically-accented beat patterns (e.g., Iversen et al., 2009); taken together, this reinforces the idea that beat perception is robust from an early age (if not innate; see Winkler et al., 2009). Specifically, the children showed neural responses that fluctuated in both ERPs (with components that are typical of auditory stimulation; Ponton et al., 2000) and evoked beta and gamma activity according to the beat pattern that they heard: enhanced neural responses were found at the strong beat (i.e., the moment that the tone received the physical accent). Moreover, beyond the contribution of behaviorally measured rhythm perception skills, our measures of the differentiation of the children's neural responses in the beta and gamma bands between accented and unaccented beats in initial position (termed Beat1 effect) were found to correlate and predict variance in spoken syntactic abilities. This was especially the case for task items requiring more refined complex syntactic operations (i.e., generation of multi-clausal sentences with dependency relations), for which the most influential predictors were our beta and gamma neural measures. The hierarchical regression model also included age, nonverbal IQ, music experience, and SES variables, ruling out the possibility that these results are due only to general maturity and cognitive effects or to environmental influences.

Our study is the first to our knowledge to show that individual differences in expressive syntactic performance are predicted by neural – beyond and complementarily to behavioral – measures of rhythm in children. The unique variance explained by the beta and gamma neural measures recorded around the onset of the first tone, which lies between 19 and 29.2%, significantly contributes to the ability of the model to predict the children's syntactic performance

scores, for a total of variance explained that reaches 70.8% in one case (see Model 2 on SPELT-3 total scores in Table 4). Importantly, this indicates that individual differences in grammar skills may be predicted by passively collected neural measures; the fact that beat perception is already measurable in newborns (Winkler et al., 2009) suggests that such paradigms may also be used to investigate grammatical development in children from a very early age.

Contrary to our expectations, larger neural activity around the onset of the second tone seemed not to reflect better syntactic encoding: activity in this latency did not significantly contribute to explain variance in the children's grammar scores; moreover, the gamma results showed that the measures of the differentiation of the children's neural responses between accented and unaccented beats in second position (termed Beat2 effect) were not significantly associated with their syntactic scores. In other words, this means that those children who better discriminated the difference between accented and unaccented beats on the second tone did not necessarily exhibit stronger grammar abilities. These results, together with those showing the children's facilitation in relation to the first tone, could potentially be related to the most common stress patterns found in English. The strong-weak (or trochaic) pattern in speech (Cutler & Carter, 1987) is preferred by English speakers already at infancy (Echols et al., 1997; Jusczyk et al., 1993) and is acquired earlier than weak-strong (iambic) patterns (Ballard et al., 2012). Children's ability to discriminate accent information on the second tone may thus be less relevant to linguistic structure processing in English. Future research investigating other languages will help clarify whether this is the case. Prior work also found that responses to the first tone were larger, suggesting serial-order effects also consistent with the above explanation (Iversen, et al, 2009).

The significant brain-behavior correlations observed in relation to the evoked time-frequency neural activity indicate that investigating high-frequency phase-locked oscillatory activity provides new insight into neural markers that could help explain behavioral associations between rhythm processing and grammar performance reported elsewhere (Gordon, Jacobs, et al., 2015; Gordon, Shivers, et al., 2015; Lee et al., 2020; Politimou et al., 2019; Swaminathan &

Schellenberg, 2019). In the context of meter, these findings align with prior findings of beta (which is thought to be closely related to rhythmic processing; Fujioka et al., 2012) and to beat perception (Cirelli et al., 2016; Flaten et al., 2022; Fujioka et al., 2015), as well as with prior findings of gamma activity (which has been shown to track hierarchical linguistic structures: Ding et al., 2015). It should be noted that the beta band is also thought to play an important role in coordinating the entrainment of the auditory and motor cortices (Bartolo et al., 2014), which are important for both language and rhythm. Several neurophysiological processes therein may contribute to these brain-behavioral associations, including sensorimotor coupling in auditory-motor networks and fine-grained auditory processing (Fiveash et al., 2021; Ladányi, Persici, et al., 2020). Optimal entrainment between the auditory and motor cortices may facilitate rhythm and language processing, possibly by enhancing predictions about sensory events (Kotz et al., 2009, Kotz & Schmidt-Kassow, 2015).

Beta and gamma neural activity have indeed both been associated with predictive processes regarding the timing (when) and content (what) of upcoming events (Arnal & Giraud, 2012; Leventhal et al., 2012; Zanto et al., 2005), as they are thought to reflect synchronization of neuronal populations during sensory processing of regular, predictive information (Arnal & Giraud, 2012), which is possibly further shaped by top-down, learned modulation from the motor system (Iversen et al., 2009; Patel & Iversen, 2014). Beyond sensory processing of the physical accents, it appears in the current study that more efficient synchronization and beat structure differentiation in the beta and gamma bands is associated with extraction and parsing of hierarchically complex structures (Ding et al., 2016). These new EEG results, and the rapid time course at which they unfold in tracking the onset of a musical beat, complement recent fMRI meta-analysis findings of overlapping neural resources of complex syntax and musical rhythm in adulthood (Heard & Lee, 2020). The findings of the current study are particularly relevant in consideration of the ontogeny of complex syntax use, which has a notably protracted developmental acquisition throughout school-age in children with typical development (Vasilyeva et al., 2008) and becomes increasingly vital for

the communication of complex academic material, life skills, and social relationships (Brimo et al., 2017; Fujiki et al., 1999). The link between rhythm and language via neural oscillations is also reinforced by the finding that musicians – who show better endogenous neural entrainment to rhythm (Stupacher et al., 2017) – find it easier to acquire new hierarchical structures in an artificial language (Brod & Opitz, 2012). The association between hierarchical structure extraction and parsing in rhythm and language fit well in the context of evolutionary arguments as to the role of rhythm in human communication and interaction (Honing, 2018; Patel & Iversen, 2014; Savage et al., 2020). Humans appear to be naturally disposed to perceiving, producing, and appreciating rhythms across a variety of contexts (Savage et al., 2015), including verbal and nonverbal social interaction (Cirelli et al., 2018). In children, the predisposition to perceive, extract, and manipulate hierarchical information may guide language learning by facilitating scaffolding of incoming input into distinct language units (Flaten et al., 2022) and thus ease processing and manipulation of complex linguistic information.

To conclude, the present study showed how individual differences in neural markers of beat perception predict individual differences in expressive grammar in six-year-old children. Individual differences in mastery of complex syntax structure were especially predicted by beta band activity. In line with previous research (e.g., Politimou et al., 2019; Swaminathan & Schellenberg, 2019; Woodruff Carr et al., 2014), the present findings suggest that precise neural encoding of temporally organized rhythmic structure may reflect a mechanism biologically related to typical language development and acquisition. Impairment of mechanisms linked to neural markers of rhythm may eventually have critical implications for bolstering earlier identification and treatment of developmental speech and language disorders (see the Atypical Rhythm Risk Hypothesis by Ladányi, Persici, et al., 2020). It is important to note that future investigations in a larger sample size and utilizing an in-depth, comprehensive battery of complex syntax language assessments, investigating both comprehension and production, are warranted to assess the generalizability of these results. The inclusion of imagined beat conditions in the future may also enlarge our

understanding of language processes: in the present study we only examined passive (and possibly pre-attentive) evoked responses, but studies have suggested that attentive and top-down processes also contribute to the discovery of temporal structure and provide potential additional vistas that might reveal novel insights into the development of the neural underpinnings of the temporal processing of language. The inclusion of such conditions would also help clarify whether the neural responses observed in this study are partly influenced by the physical properties of the stimuli. Although previous work suggest that these types of responses are neural correlates of beat tracking (Iversen et al., 2009; Kasdan et al., 2020), possible effects due to perception of intensity cannot be excluded and direct claims about predictive processing cannot be made. Research with other languages may also be of help in investigating whether these results are language-specific or generalizable across different languages. Nonetheless, the current study is one of the few ones so far to apply an individual differences approach toward understanding of children's neural activity during a musical task, and furthermore to show, in a developmental population, evidence of a link between individual differences in neural activity and in a trait in a different domain. These promising findings suggest that this approach to rhythmic neural processing with EEG in children may not only be a passive, implicit, rapid, and relatively inexpensive way to assay a particular dimension of musical beat processing that appears to have strong links with spoken language development. Similar approaches may also serve as an important tool for predicting individual differences in complex language use in school-age children with a wide range of language skills.

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Conflict of Interest Statement

All authors declare no competing interests.

Author Contributions

Conceptualization of Study: RLG, JDM, SAK. Study Design: RLG, JDM, SAK, APK, VP, SDB. Materials and Methods: RLG, JDM, JRI, SAK. Data Analysis: VP, RLG, SDB. Interpretation of Primary Findings: VP, RLG, JDM. Writing, Editing, and Reviewing Drafts: VP, RLG, JDM, SAK, APK, JRI, SDB.

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Supplementary material

Table 1S

Characteristics of the significant clusters identified by cluster-based permutation tests of Event-Related Potentials during the EEG rhythm task, and their significant associations with individual differences in language skills

	SPELT-3		Transformation		Complex	
	total				Syntax	
	$r_{(s)}$	p	$r_{(s)}$	p	$r_{(s)}$	p
ERP-Beat1effect-early-negativity-frontal	-0.03	0.948	0.05	0.910	-0.05	0.910
ERP-Beat1effect-early-positivity-posterior	0.14	0.892	0.09	0.910	0.09	0.910
ERP-Beat2effect-late-negativity-frontal1	0.21	0.793	0.10	0.910	0.05	0.910
ERP-Beat2effect-late-positivity-posterior	0.07	0.910	0.00	1.000	0.05	0.910
ERP-Beat2effect-late-negativity-frontal2	0.16	0.853	-0.09	0.910	0.29	0.587

Note. Spearman correlations included age, nonverbal IQ, music experience, and maternal education as covariates. P-values were adjusted for multiple comparisons using the Benjamini-Hochberg correction. $*p < .05$, $**p < .01$, $***p < .001$.

Table 2S

Hierarchical regressions model fit and summary

Dependent Variable	Model	Model Fit						Predictor	Standardized beta	S.E.	t-value	p-value
		<i>F</i>	<i>df</i>	<i>p</i>	Adjusted R^2	AIC	BIC					
SPELT-3 total score	Model 1	4.799	5, 19	0.005	0.442	63.509	72.041	Intercept	0.000	0.149	0.000	1.000
	(base model)							Age	0.071	0.168	0.423	0.677
								Nonverbal IQ	0.063	0.165	0.382	0.707
								Music Experience	0.091	0.158	0.575	0.572
								Maternal Education (SES)	0.121	0.158	0.763	0.455
								Rhythm Composite Score	0.658	0.180	3.664	0.002
								Intercept	0.000	0.153	0.000	1.000
								Age	0.059	0.173	0.341	0.737
								Nonverbal IQ	0.082	0.173	0.473	0.642
								Music Experience	0.087	0.162	0.538	0.597
								Maternal Education (SES)	0.125	0.162	0.775	0.448
								Rhythm Composite Score	0.660	0.183	3.597	0.002
								ERP-Beat1 effect-early-negativity-frontal	-0.079	0.161	-	0.630
											0.491	
Model 2	Model 2	3.880	6, 18	0.012	0.419	65.177	74.928	Intercept	0.000	0.153	0.000	1.000
	Model 3	3.928	6, 18	0.011	0.423	65.004	74.755	Intercept	0.000	0.152	0.000	1.000
Model 3	Model 3							Age	0.047	0.175	0.271	0.790

							Nonverbal	0.084	0.171	0.492	0.629
							IQ				
							Music	0.089	0.161	0.551	0.588
							Experience				
							Maternal	0.123	0.161	0.764	0.455
							Education				
							(SES)				
							Rhythm	0.652	0.183	3.563	0.002
							Composite				
							Score				
							ERP-	0.099	0.163	0.606	0.552
							Beat1effect-				
							early-				
							positivity-				
							posterior				
Model	3.845	6,	0.012	0.416	65.305	75.056	Intercept	0.000	0.153	0.000	1.000
4		18									
							Age	0.071	0.171	0.412	0.686
							Nonverbal	0.087	0.180	0.484	0.634
							IQ				
							Music	0.097	0.163	0.594	0.560
							Experience				
							Maternal	0.120	0.162	0.741	0.468
							Education				
							(SES)				
							Rhythm	0.644	0.188	3.426	0.003
							Composite				
							Score				
							ERP-	0.064	0.168	0.384	0.705
							Beat2effect-				
							late-				
							negativity-				
							frontal1				
Model	3.807	6,	0.013	0.412	65.442	75.193	Intercept	0.000	0.153	0.000	1.000
5		18									
							Age	0.075	0.173	0.435	0.669
							Nonverbal	0.051	0.178	0.285	0.779
							IQ				
							Music	0.088	0.163	0.538	0.597
							Experience				

								Maternal Education (SES)	0.124	0.163	0.760	0.457
								Rhythm Composite Score	0.665	0.187	3.563	0.002
								ERP-Beat2effect-late-positivity-posterior	-0.037	0.168	-	0.828
											0.220	
Model	3.974	6,	0.010	0.426	64.836	74.587	Intercept	0.000	0.151	0.000	1.000	
6		18					Age	0.054	0.172	0.313	0.758	
							Nonverbal IQ	0.119	0.185	0.641	0.530	
							Music Experience	0.041	0.176	0.235	0.817	
							Maternal Education (SES)	0.103	0.162	0.634	0.534	
							Rhythm Composite Score	0.634	0.186	3.416	0.003	
							ERP-Beat2effect-late-negativity-frontal2	0.136	0.194	0.701	0.492	
Transformation	Model	3.940	5,	0.013	0.380	66.140	74.672	Intercept	0.000	0.157	0.000	1.000
	1		19				Age	0.443	0.177	2.509	0.021	
	(base model)						Nonverbal IQ	-0.242	0.174	-	0.180	
							Music Experience	0.116	0.167	0.692	0.497	
							Maternal Education (SES)	0.132	0.167	0.794	0.437	

							Rhythm	0.417	0.189	2.204	0.040
							Composite				
							Score				
Model	3.210	6,	0.025	0.356	67.736	77.487	Intercept	0.000	0.161	0.000	1.000
2		18					Age	0.457	0.182	2.514	0.022
							Nonverbal	-0.263	0.182	-	0.164
							IQ			1.450	
							Music	0.120	0.170	0.705	0.490
							Experience				
							Maternal	0.127	0.170	0.745	0.466
							Education				
							(SES)				
							Rhythm	0.416	0.193	2.155	0.045
							Composite				
							Score				
							ERP-	0.092	0.170	0.542	0.595
							Beat1 effect-				
							early-				
							negativity-				
							frontal				
Model	3.123	6,	0.028	0.347	68.090	77.841	Intercept	0.000	0.162	0.000	1.000
3		18					Age	0.451	0.186	2.426	0.026
							Nonverbal	-0.249	0.182	-	0.189
							IQ			1.365	
							Music	0.116	0.171	0.678	0.506
							Experience				
							Maternal	0.132	0.171	0.769	0.452
							Education				
							(SES)				
							Rhythm	0.420	0.195	2.155	0.045
							Composite				
							Score				
							ERP-	-0.033	0.173	-	0.851
							Beat1 effect-			0.190	
							early-				
							positivity-				
							posterior				
	3.129		0.028	0.347	68.065	77.816	Intercept	0.000	0.162	0.000	1.000

Model 4	3.154	6, 18	0.027	0.350	67.963	77.714	Age	0.443	0.181	2.445	0.025
							Nonverbal	-0.226	0.190	-	0.250
							IQ			1.189	
							Music	0.119	0.172	0.693	0.497
							Experience				
							Maternal	0.132	0.171	0.771	0.451
							Education				
							(SES)				
							Rhythm	0.408	0.199	2.055	0.055
							Composite				
Model 5	3.184	6, 18	0.026	0.353	67.843	77.594	Score				
							ERP-	0.041	0.177	0.233	0.818
							Beat2effect-				
							late-				
							negativity-				
							frontal1				
							Intercept	0.000	0.161	0.000	1.000
							Age	0.451	0.182	2.476	0.023
							Nonverbal	-0.263	0.188	-	0.178
							IQ			1.402	
Model 6	3.184	6, 18	0.026	0.353	67.843	77.594	Music	0.110	0.172	0.641	0.530
							Experience				
							Maternal	0.138	0.171	0.804	0.432
							Education				
							(SES)				
							Rhythm	0.428	0.196	2.183	0.043
							Composite				
							Score				
							ERP-	-0.063	0.177	-	0.724
							Beat2effect-			0.358	
Model 6	3.184	6, 18	0.026	0.353	67.843	77.594	late-				
							positivity-				
							posterior				
Model 6	3.184	6, 18	0.026	0.353	67.843	77.594	Intercept	0.000	0.161	0.000	1.000
							Age	0.455	0.182	2.498	0.022
							Nonverbal	-0.281	0.197	-	0.170
Model 6	3.184	6, 18	0.026	0.353	67.843	77.594	IQ			1.429	

								Music	0.151	0.187	0.808	0.430									
								Experience													
								Maternal	0.145	0.172	0.840	0.412									
								Education													
								(SES)													
								Rhythm	0.435	0.197	2.207	0.041									
								Composite													
								Score													
								ERP-	-0.096	0.206	-	0.648									
								Beat2effect-	0.464												
								late-													
								negativity-													
								frontal2													
Complex	Model	3.135	5,	0.031	0.308	68.887	77.419	Intercept	0.000	0.166	0.000	1.000									
Syntax	1		19																		
	(base																				
	model)																				
								Age	0.311	0.187	1.669	0.111									
								Nonverbal	0.173	0.184	0.944	0.357									
								IQ													
								Music	0.261	0.176	1.482	0.155									
								Experience													
								Maternal	0.257	0.176	1.459	0.161									
								Education													
								(SES)													
								Rhythm	0.276	0.200	1.378	0.184									
								Composite													
								Score													
	Model	2.716	6,	0.047	0.300	69.811	79.562	Intercept	0.000	0.167	0.000	1.000									
	2		18																		
													Age	0.288	0.190	1.517	0.147				
													Nonverbal	0.210	0.189	1.111	0.281				
								IQ													
								Music	0.254	0.178	1.428	0.171									
								Experience													
								Maternal	0.266	0.177	1.502	0.151									
								Education													
								(SES)													
								Rhythm	0.278	0.201	1.382	0.184									
								Composite													
								Score													

							ERP-	-0.158	0.177	-	0.385
							Beat1effect-			0.890	
							early-				
							negativity-				
							frontal				
Model	2.699	6,	0.048	0.298	69.883	79.634	Intercept	0.000	0.168	0.000	1.000
3		18					Age	0.275	0.193	1.425	0.171
							Nonverbal	0.207	0.189	1.093	0.289
							IQ				
							Music	0.258	0.178	1.452	0.164
							Experience				
							Maternal	0.261	0.177	1.469	0.159
							Education				
							(SES)				
							Rhythm	0.266	0.202	1.318	0.204
							Composite				
							Score				
							ERP-	0.154	0.180	0.859	0.402
							Beat1effect-				
							early-				
							positivity-				
							posterior				
Model	2.505	6,	0.061	0.273	70.752	80.503	Intercept	0.000	0.170	0.000	1.000
4		18					Age	0.311	0.191	1.628	0.121
							Nonverbal	0.195	0.201	0.972	0.344
							IQ				
							Music	0.266	0.182	1.468	0.159
							Experience				
							Maternal	0.256	0.180	1.421	0.173
							Education				
							(SES)				
							Rhythm	0.262	0.209	1.252	0.227
							Composite				
							Score				
							ERP-	0.058	0.187	0.312	0.758
							Beat2effect-				
							late-				

							negativity- frontal1				
Model	2.497	6,	0.062	0.272	70.789	80.540	Intercept	0.000	0.171	0.000	1.000
5		18					Age	0.305	0.193	1.585	0.130
							Nonverbal	0.190	0.198	0.958	0.351
							IQ				
							Music	0.266	0.182	1.463	0.161
							Experience				
							Maternal	0.253	0.181	1.394	0.180
							Education				
							(SES)				
							Rhythm	0.267	0.208	1.288	0.214
							Composite				
							Score				
							ERP-	0.050	0.187	0.266	0.793
							Beat2effect-				
							late-				
							positivity-				
							posterior				
Model	2.918	6,	0.036	0.324	68.942	78.693	Intercept	0.000	0.164	0.000	1.000
6		18					Age	0.279	0.186	1.499	0.151
							Nonverbal	0.278	0.201	1.380	0.184
							IQ				
							Music	0.168	0.191	0.882	0.390
							Experience				
							Maternal	0.224	0.176	1.271	0.220
							Education				
							(SES)				
							Rhythm	0.229	0.201	1.140	0.269
							Composite				
							Score				
							ERP-	0.254	0.211	1.207	0.243
							Beat2effect-				
							late-				
							negativity-				
							frontal2				

Note. Significant effects are in bold. Adjusted R^2 indicates the proportion of variance explained adjusted for the number of predictors in the model. AIC = Akaike Information Criterion. BIC = Bayesian Information Criterion.

Table 3S

Spearman correlation test results between activity in beta and gamma and between activity to the first vs. the second tone within each frequency band

Neural evoked variables		1	2	3
1	EEG-beta-Beat1 effect cluster			
2	EEG-beta-Beat2 effect cluster	0.25		
3	EEG-gamma-Beat1 effect cluster	0.37	0.17	
4	EEG-gamma-Beat2 effect cluster	0.10	0.44*	-0.20

Note. Spearman correlations included age, nonverbal IQ, music experience, and maternal education as covariates. P-values were adjusted for multiple comparisons using the Benjamini-Hochberg correction. * $p < .05$.

Table 4S

Characteristics of the significant clusters identified by cluster-based permutation tests of Event-Related Potentials (ERP) and of beta and gamma evoked activity during the EEG rhythm task and including all the trials that participants received (including extra epochs)

Cluster	Latency	Cluster p-value
ERP-Beat1effect-early-negativity-frontal	-46 to 52 ms	.009
ERP-Beat1effect-early-positivity-posterior	-32 to 56 ms	.020
ERP-Beat2effect-late-negativity-frontal1	222 to 430 ms	< .001
ERP-Beat2effect-late-positivity-posterior	216 to 408 ms	< .001
ERP-Beat2effect-late-negativity-frontal2	424 to 500 ms	.026
EEG-beta-Beat1effect	-100 to 148 ms	< .001
EEG-beta-Beat2effect	208 to 342 ms	.004
EEG-gamma-Beat1effect	58 to 124 ms	.020
EEG-gamma-Beat2effect	228 to 316 ms	.001