

Oscillatory Attention in Groove

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Abstract

Attention is not constant but rather fluctuates over time and these attentional fluctuations may prioritize the processing of certain events over others. In music listening, the pleasurable urge to move to music (termed ‘groove’ by music psychologists) offers a particularly convenient case study of oscillatory attention because it engenders synchronous and oscillatory movements which also vary predictably with stimulus complexity. In this study, we simultaneously recorded pupillometry and scalp electroencephalography (EEG) from participants while they listened to drumbeats of varying complexity that they rated in terms of groove afterwards. Using the intertrial phase coherence of the beat frequency, we found that while subjects were listening, their pupil activity became entrained to the beat of the drumbeats and this entrained attention persisted in the EEG even as subjects imagined the drumbeats continuing through subsequent silent periods. This entrainment in both the pupillometry and EEG worsened with increasing rhythmic complexity, indicating poorer sensory precision as the beat became more obscured. Additionally, sustained pupil dilations revealed the expected, inverted U-shaped relationship between rhythmic complexity and groove ratings. Taken together, this work bridges oscillatory attention to rhythmic complexity in relation to musical groove.

Keywords: {attention, groove, EEG, pupillometry, rhythmic complexity}

Oscillatory Attention in Groove

Attention is a limited cognitive resource and so it must be efficiently allocated at strategic moments in time; we cannot pay attention to everything all at once all of the time as well as to the same degree in a continuously sustained manner (James, 1890). Dynamic attending theory (DAT) proposes that attention is allocated via endogenous oscillations whose peaks become aligned to relevant stimuli in the environment for enhanced processing, while less relevant stimuli occurring in troughs are processed more poorly (Jones, 1976, 2018; Jones & Boltz, 1989; Large & Jones, 1999). Naturally, this theory offers a particularly attractive account for the perception of repetitive stimuli, which are by definition, oscillatory themselves. Rhythm and meter perception in music have been an especially useful case study for investigating dynamical systems since musical rhythms are highly ecological stimuli and relatively easy to quantify in oscillatory terms (e.g., frequency, phase) (Danielsen, 2018; Drake et al., 2000; Jones, 1987; Large, 2008; Large & Palmer, 1996, 2002; Large & Snyder, 2009; Skaansar et al., 2019). Furthermore, some musical rhythms even spontaneously engender synchronous movements in their listeners in a pleasurable experience termed “groove” by music psychologists (Janata et al., 2012; Madison, 2006), providing researchers with a behavioral correlate of entrained oscillators (Repp, 2005; Repp & Su, 2013).

Both groove and sensorimotor synchronization vary predictably with rhythmic complexity, albeit in different ways. While movement synchronization clearly worsens with increasing rhythmic complexity (Chen et al., 2008; Franěk et al., 1987, 1988; Mathias et al., 2020; Skaansar et al., 2019; Snyder et al., 2006; Spiech, Hope, et al., 2022), groove seems to exhibit an inverted U-shaped relationship to rhythmic complexity (Matthews et al., 2019, 2022; Pando-Naude et al., 2023; Sioros et al., 2014; Spiech, Hope, et al., 2022; Spiech, Sioros, et al.,

2022; Stupacher et al., 2022; Witek et al., 2014; Zalta et al., 2023). Recently, this pattern of results has been explained in terms of DAT (Zalta et al., 2023). Put simply, neural oscillators in the auditory cortex can entrain to simple rhythms without the need for secondary oscillators, e.g., in the (pre)motor cortices, whose activity would be redundant. At moderate levels of rhythmic complexity, synchronous movements could encode temporal predictions about the beat and meter to strengthen auditory oscillations that are beginning to weaken. However, beyond a certain threshold of complexity, both auditory and motor oscillators could no longer reliably lock to the music's beat and so both movement synchronization performance and groove might become minimal.

While many of the above studies have demonstrated that sensory and motor entrainment worsen with increasing rhythmic complexity, none have thus far connected this relationship directly to the neurophysiological and behavioral correlates of groove. Thus, this study attempts to do precisely that using both EEG and pupillometry.

The Present Study

To accomplish this, we recorded oscillatory attention using both pupillometry and scalp electroencephalography (EEG) while participants listened to and rated three drumbeats of varying rhythmic complexity. Both methods have successfully been used to track the brain's synchronization to music (Doelling & Poeppel, 2015; Fink et al., 2018; Nozaradan et al., 2016), but as of the time of writing, sustained pupillary activity remains the only neurophysiological correlate of groove ratings (Spiech, Sioros, et al., 2022). Here, we measure attentional entrainment using the intertrial phase coherence (ITC) in both pupil activity and EEG at the beat frequency since it is “much more sensitive to stimulus-synchronized neural activity” than spectral power (Ding & Simon, 2013) and is linked to attention-enhanced sensory processing

(Arnal & Giraud, 2012; Lakatos et al., 2008, 2013; Ponjavic-Conte et al., 2012). We hypothesized that ITC would decrease with increasing rhythmic complexity, reflecting the auditory system's worsening entrainment to the beat. Sustained pupillary activity, on the other hand, was expected to exhibit the same inverse U-relationship with rhythmic complexity as we had previously observed in our lab.

Methods

Participants

A convenience sample of 30 healthy participants (13 women; 1 left handed) provided informed consent in compliance with the ethical approval granted by the Department of Psychology's internal review board for research ethics at the University of Oslo (reference number 8131575). Participants were compensated with a 200 NOK (~\$20) gift card for their participation. The average age of our sample was 28.37 (range: 20-56, SD: 7.73 years) and they reported listening to music an average of 16.83 hours per week (range: 2-80, SD: 17.82 hours). Of our 30 participants, 17 reported some amount of formal musical training (mean: 12.59, range: 3-30, SD: 7.08 years) and 18 reported the ability to play at least one type of instrument (mean: 1.83, range: 1-4, SD: 0.92 types of instrument). Twelve of these participants played string instruments, ten played the piano or keyboard, five played percussion instruments, three played brass instruments, and three sang for an average of 4.28 hours per week (range: 0-17, SD: 5.21 hours). Participants were confirmed to have normal beat perception abilities (i.e., none were beat deaf) using the Computerised Adaptive Beat Alignment Test (Harrison & Müllensiefen, 2018a, 2018b).

Drumbeat Stimuli

To measure the effect of rhythmic complexity on entrained neurophysiological signals, we used three drumbeats of Low, Mid, and High Rhythmic Complexity from a previous study in our lab (Spiech, Sioros, et al., 2022). These three drumbeats (of the original six) were selected because they elicited the maximal differences in ratings of urge to move and liking and were controlled to contain the same number of events at the same metrical level (that of the quaver). Each drumbeat consisted of two-bar patterns at 100 beats per minute. To observe differences in endogenous neural entrainment, the stimuli were looped eight times with a 100 ms fade-out applied to the final loop to prevent clipping upon the onset of the subsequent silent window. This silent window lasted one full pattern-length during which the subjects were tasked with imagining the drumbeat continuing for a total duration of 43.2 seconds (38.4 seconds of drumbeats playing + 4.8 seconds of silence). Crucial for our EEG analyses, this silent window allowed us to interpret any neural entrainment here as an endogenous attentive process rather than the product of evoked auditory responses.

Using drumbeats rather than sine waves or series of tones as is more common in EEG research provided us with more ecological validity without melodic or harmonic confounds. Additionally, an important aspect of the rhythmic complexity of drumbeats is pulse clarity, which can be quantified by simply counting the total deviations from isochrony at the beat level of the pattern. As can be seen in Figure 1, the drumbeats were made increasingly complex by displacing more kicks and snares (represented as K and S in Figure 1a, respectively) from their isochronous positions in the Low Rhythmic Complexity condition. A spectral analysis of the event onsets (shown in Figure 1b) demonstrates that this manipulation successfully decreased spectral power at the beat frequency (1.67 Hz).

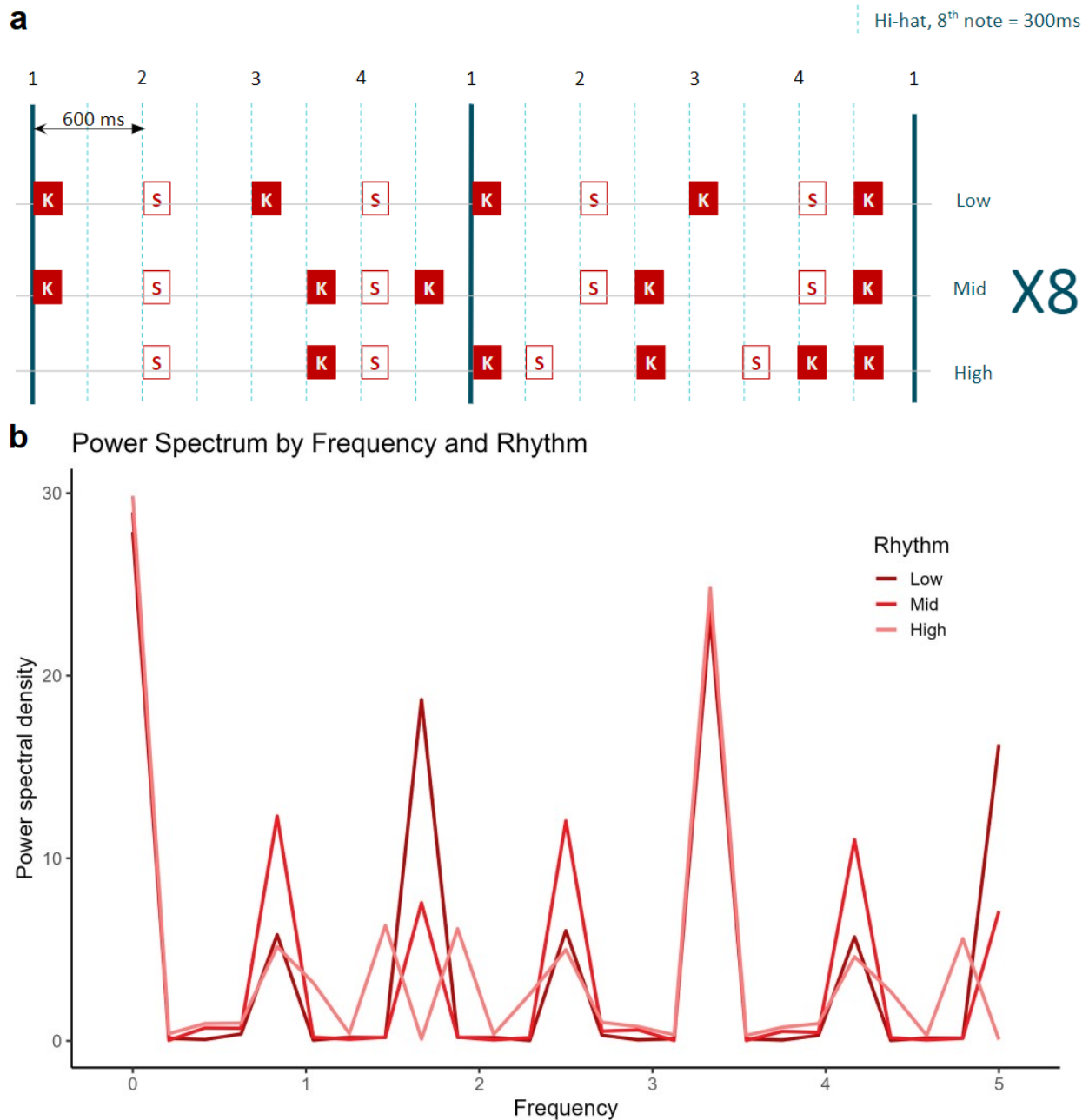


Figure 1. Drumbeat stimuli used in the experiment. A. Schematic of the three drumbeats with K denoting kick drum hits, S denoting snare drum hits, and dashed lines representing hi-hat hits. Solid vertical lines denote bar boundaries and numbers at the top of the plot describe metric positions. Rhythms were made increasingly complex by shifting the positions of kicks and snare hits from their isochronous positions in the Low Rhythmic Complexity condition. B. Spectral

analysis of the drumbeat onsets demonstrating that displacing kicks and snares from the beat decreased spectral power at the beat frequency (1.67 Hz).

Procedure

Subjects were seated in a well-lit, windowless room 70 cm away from a 22-inch LED monitor flanked by two Genelec speakers (model 8030W) with a subwoofer underneath the desk to enhance bass frequencies since previous research suggests it's important for groove (Hove et al., 2019; Lenc et al., 2018; Stupacher et al., 2016). After providing us with their demographics information and calibrating the eye-tracker, participants were instructed to listen to each drumbeat and rate their Urge to Move (“I did not want to move at all” vs. “I wanted to move a lot” where movement explicitly included tapping or nodding to the beat), Pleasure (“I did not enjoy it at all” vs. “I enjoyed it a lot”), and a catch question about Perceived Energy (“The drumbeat was very calm” vs. “The drumbeat was very excited”) using visual analog scales after each trial.

A single trial began with one second of silence with a black ring presented on a gray background in the center of the screen which subjects were instructed to fixate within to serve as a trial-level baseline for the pupillometry. After this brief silent baseline window, one of the three drumbeats was played with its subsequent, silent window for endogenous entrainment. Drumbeats were presented randomly within each Block, which consisted of a single presentation of each of the three drumbeats. The entire experiment consisted of 15 Blocks for a total of 45 trials and was programmed using Psychtoolbox-3 for MATLAB (Kleiner et al., 2007). Finally,

participants completed the Computerised Adaptive Beat Alignment Test (CA-BAT). With self-paced breaks and EEG preparation, each session lasted around one and a half hours.

Behavioral Data Processing and Analysis

Participants ratings of Urge to Move, Pleasure, and Perceived Energy were z-scored by subject to control for differences in the way that they used the visual analog scales. Repeated measures analyses of variance (ANOVAs) were conducted separately for each rating to replicate findings that the Urge to Move and Pleasure are highest for moderate levels of Rhythmic Complexity. If necessary, these tests were sphericity-corrected according to Girden's recommendations (i.e., Greenhouse-Geisser if $\epsilon < 0.75$ and Huynh-Feldt if $\epsilon > 0.75$) (Girden, 1992; Greenhouse & Geisser, 1959; Huynh & Feldt, 1976). Given the monotonous nature of the task, only the first three Blocks of ratings were analyzed since, after this point, participants did not want to move or enjoy any of the three drumbeats. Significant omnibus tests were followed by post-hoc Welch's paired-sample t-tests corrected for multiple comparisons using the false discovery rate (FDR) method proposed by Benjamini and Hochberg (Benjamini & Hochberg, 1995).

Pupillometry Recording, Processing, and Analysis

A tripod-mounted EyeLink Portable Duo was placed beneath the monitor to continuously sample participants' pupil diameters at 500 Hz using the stationary mode with their heads mounted on a chinrest. At the start of the experiment (and after head repositioning during breaks if needed), participants completed a five-point (cross-shaped) calibration procedure. Recorded pupil data was exported offline from EyeLink Data Viewer (*EyeLink Data Viewer*, 2018) for preprocessing with custom R scripts and functions from the "pupillometry", "gazeR", and "signal" packages in R (Geller et al., 2020; signal developers, 2014; Tsukahara, 2020).

First, the pupil time series for each participant's right eye were read in and timelocked to the stimuli onsets. Blinks were removed along with the preceding and succeeding 100 ms to exclude artifacts caused by partial occlusions of the pupil by the eyelid. The pupil time series was then smoothed using a 1000 ms moving average and gaps smaller than 1000 ms were interpolated using cubic splines. Each trial was then baseline-corrected by subtracting the median pupil value recorded from the 1000 ms of silence preceding drumbeat onsets to remove random fluctuations in pupil size between trials (Laeng & Alnaes, 2019; Laeng & Sulutvedt, 2014). Surviving artifacts were removed in a tripartite fashion: trials with more than 33% of missing data were discarded, samples with rapid pupil size changes were detected and eliminated using the median absolute deviation of the dilation speed time series with a constant of 16 as suggested by Kret & Sjak-Shie (Kret & Sjak-Shie, 2019), and visual inspection of a histogram of all remaining pupil sizes as recommended by Mathôt and colleagues (Mathôt et al., 2018). Finally, the cleaned pupil data was averaged into 100 ms bins.

To investigate potential oscillatory dynamics in the pupil data, some additional processing was needed. The first loop and silent window needed to be discarded because of the orienting responses elicited by stimulus onset and offset. Then, to remove signal drift, each trial was high-pass filtered with a third order Butterworth filter at 0.05 Hz, and then each trial for each subject was z-scored according to the preprocessing steps employed by Fink and colleagues (Fink et al., 2018). Finally, the second loop needed to be discarded due to extreme drift that survived the high-pass filter. The remaining six loops' time series were timelocked to the start of the repetition to obtain evoked pupil dilations for each of the three drum patterns. Fourier series were extracted from these time series using a fast Fourier transform (Cooley & Tukey, 1965) so that the intertrial phase coherence of the beat frequency (1.67 Hz) could be compared across

Rhythmic Complexity. Each subject's normalized pupil data was also averaged by Rhythmic Complexity to investigate its effect on overall attentional deployment. Both the averaged evoked dilations and the beat frequency intertrial phase coherence were analyzed with repeated measures ANOVAs and corrected for sphericity in a similar manner as the behavioral data if necessary. Finally, FDR-corrected Welch's paired-sample t-tests were used for post-hoc tests when significant effects were found.

EEG Recording, Processing, and Analysis

EEG was recorded with 64 channels at a sampling rate of 1024 Hz using a BioSemi Active Two Ag-AgCl electrode system (BioSemi, Amsterdam, The Netherlands). Electrodes were placed according to the International 10-20 system (Jasper, 1958) with four pairs of additional electrodes placed 1) on each earlobe for offline re-referencing, 2) on the medial and lateral heads of the dominant *triceps surae* (calf muscles) to record potential foot tapping, 3) above and below the right eye to measure blinks and vertical eye movements, 4) and lateral to the participants left and right eyes to capture horizontal eye movements.

All electrophysiological data were processed and analyzed offline using the FieldTrip Toolbox (Oostenveld et al., 2011) for Matlab (2020b, Mathworks Inc., Natick, MA, USA). Scalp EEG was re-referenced to the linked earlobes, high-pass filtered with a 0.1 Hz fourth-order Butterworth filter, detrended to remove slow linear drifts, and notch filtered at 50 Hz (along with its next five harmonics) to remove line noise. The data were then segmented into trials. For the EEG recorded while the drums were playing, segmentation began from the onset of the drumbeat until the onset of the silent window (38.4 s), while the EEG recorded during the silent window was segmented from the silent window onset to the end of the trial (4.8 s). Noisy segments (e.g., from jaw movements) and bad channels were identified by visual inspection of the trials and

removed. An independent components analysis was then conducted to identify and remove ocular artifacts (e.g., from blinks and saccades). If any bad channels were removed, they were then interpolated using spherical splines. Finally, for data recorded while the drumbeats were playing, trials were resegmented into eight equal (4.8 s) epochs corresponding to each loop of the drumbeat within the trial such that 0 now corresponded to the start of the drum pattern.

Electrical activity from the calf muscles was processed separately from other data with a 10-Hz high-pass filter and then rectified at the trial level. Data recorded while subjects listened to the drumbeats were cut into eight equal segments corresponding to each loop within each trial and re-timelocked to the start of the drum pattern.

Fourier series were extracted from cleaned electrophysiological data using multitaper time-frequency transformations with hanning tapers. Since we were interested only in low frequencies related to the musical beat, we only analyzed frequencies from 0-5 Hz in steps of 10/48 Hz to demonstrate ITC selectivity at the beat frequency (1.67 Hz). ITC at these frequencies was thus calculated at each electrode site for statistical analysis. To this end, the scalp data was subjected to a cluster-based permutations F-test with negative linear contrast coefficients (weights of 1, 0, and -1) to investigate decreasing sensory precision while controlling for multiple comparisons (Maris & Oostenveld, 2007). Specifically, Monte-Carlo estimates with 10,000 randomizations were computed with an alpha of 0.05 (tail corrected by multiplying the probability with a factor of two) and significant clusters determined by thresholding individual voxels with a critical value of 0.05 then taking the maximum of the cluster-level statistics. Following a significant cluster from the entire frequency spectrum, the analysis was repeated for only the beat frequency to test our hypothesis directly.

Given that the electrical activity from the calf was significantly lower dimensional (two electrodes vs. 64 electrodes), the ITC from this data was instead subjected to a 3x2 repeated measures ANOVAs using Rhythmic Complexity (Low, Mid, High Complexity) and Electrode (EXG7, EXG8) as factors.

Results

In the following subsections, we will present the results of the behavioral, pupillometry, and finally, the EEG analyses.

Behavioral Results - Urge to Move and Pleasure ratings elevated for moderately complex rhythms

All repeated measures ANOVAs of the ratings violated the sphericity assumption and were corrected using the Huynh-Feldt method. Small to modest effects were found for ratings of Urge to Move ($F(1.540,44.674)=4.130, p=0.032, \eta^2G=0.081$) and Pleasure ($F(1.741,50.500)=4.286, p=0.023, \eta^2G=0.096$), but not for our catch question about Perceived Energy ($F(1.720,49.886)=0.476, p=0.624, \eta^2G=0.010$). As expected, post-hoc tests revealed that these effects were driven by greatly increased ratings for the Mid Complexity drumbeat relative to the Low Complexity (Urge to Move: $t(29)=2.418, p=0.033, d=0.90$; Pleasure: $t(29)=3.085, p=0.013, d=1.15$) and High Complexity drumbeats (Urge to Move: $t(29)=3.443, p=0.005, d=1.28$; Pleasure: $t(29)=2.217, p=0.052, d=0.82$) which did not differ from each other (Urge to Move: $t(29)=0.466, p=0.644$; Pleasure: $t(29)=-0.0892, p=0.380$). Raincloud plots of the ratings analysis are depicted in Figure 2 below.

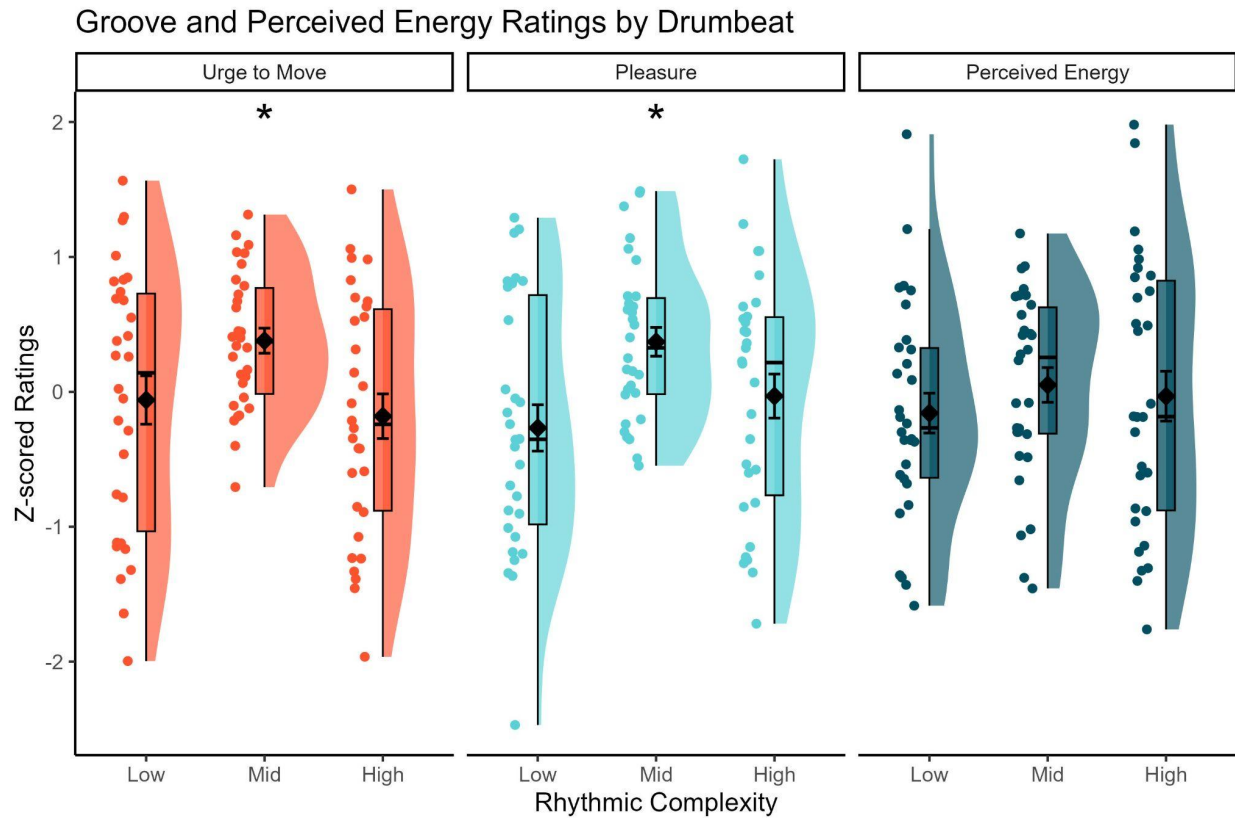


Figure 2. Groove and Perceived Energy Ratings by Rhythmic Complexity. The Mid Complexity Drumbeat was rated significantly higher in terms of the Urge to Move and Pleasure in the first three blocks of the experiment. The Low and High Complexity drumbeats, however, were not rated significantly differently. Black diamonds with error bars represent group means with their accompanying standard errors while colored points represent individual subject averages.

Pupillometry Results - Pupil dilations predictively entrain to meter and reflect groove ratings

Cleaned grand averages of the pupil traces over time by Rhythmic Complexity are plotted in Figures 3a and 3b. After removing one extreme outlier (pupil sizes were nearly four standard deviations smaller than the mean; N.B. including this outlier did not alter the pattern of results but heavily distorted the plots), the repeated measures ANOVA on average evoked pupil

dilations demonstrated a modest to large effect of Rhythmic Complexity ($F(2,56)=9.417$, $p<0.001$, $\eta^2_G=0.170$). Similar to the ratings of Urge to Move and Pleasure, post-hoc tests revealed this effect was driven by substantially larger pupil dilations for the Mid Complexity drumbeat relative to the Low Complexity ($t(28)=4.366$, $p<0.001$, $d=1.65$) and High Complexity drumbeats ($t(28)=3.393$, $p=0.003$, $d=1.28$) which did not significantly differ from each other ($t(29)=1.115$, $p=0.274$). These results are depicted in Figure 3c below.

The repeated measures ANOVA on the pupil dilations phase-locked to the beat revealed a large effect of Rhythmic Complexity ($F(2,58)=15.632$, $p<0.001$, $\eta^2_G=0.241$). As shown in Figure 4, pupil dilations entrained to the beat frequency with worsening precision as Rhythmic Complexity increased. Post-hoc tests confirmed that the Low Complexity drumbeat entrained pupil responses to the beat far more than the Mid ($t(29)=2.514$, $p=0.018$, $d=0.93$) and High Complexity drumbeats ($t(29)=5.1$, $p<0.001$, $d=1.91$), and the Mid Complexity drumbeat entrained pupil responses to the beat much more than the High Complexity drumbeat ($t(29)=3.400$, $p=0.003$, $d=1.26$) as shown in Figure 3d.

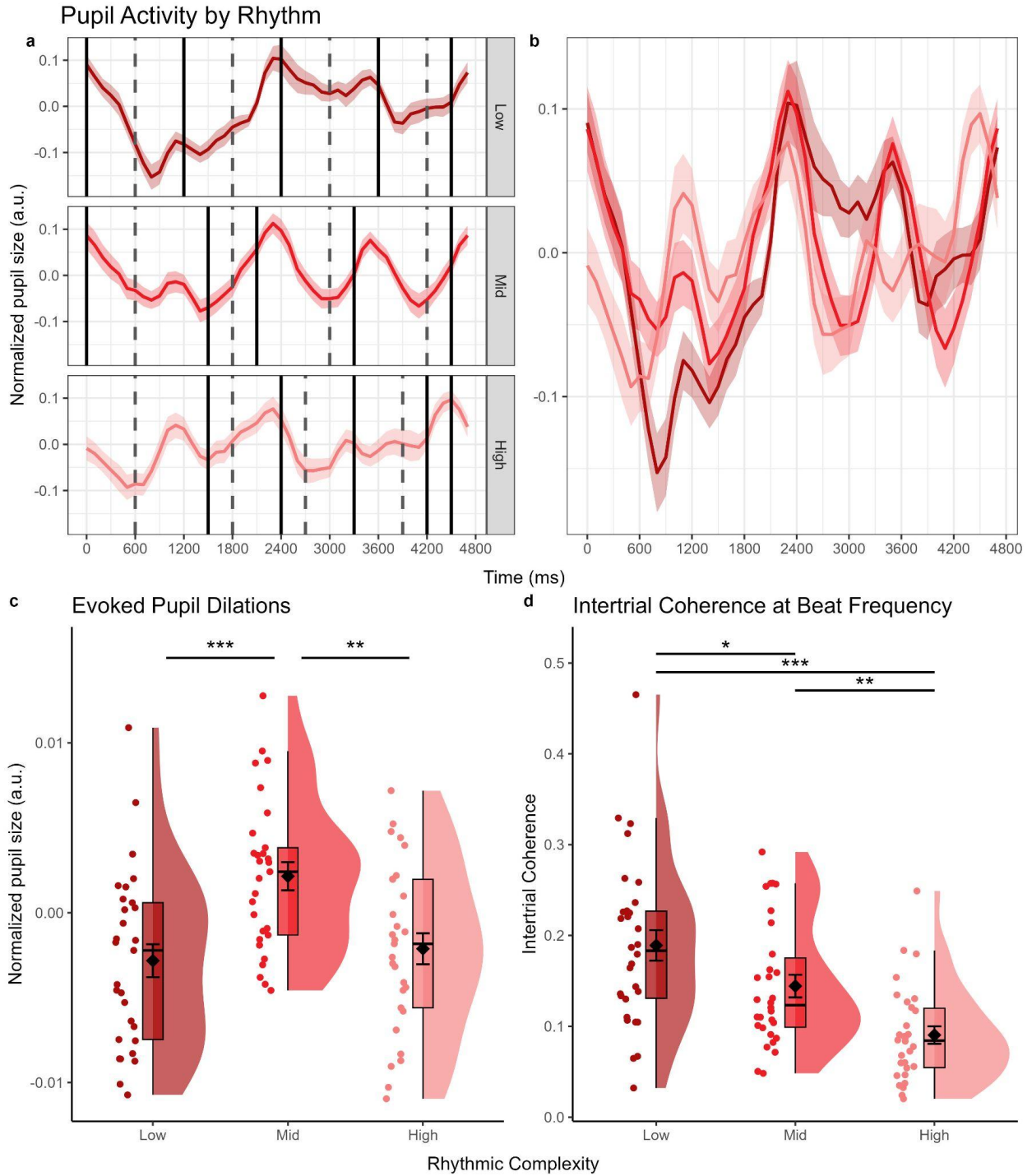


Figure 3. Pupil activity by Rhythmic Complexity. A. Cleaned grand averaged pupil traces mapped to kick drum (solid lines) and snare drum hits (dashed lines). B. Cleaned grand averaged pupil traces for all conditions directly comparing dilation magnitudes over time by Rhythmic

Complexity. C. Beat frequency ITC in the pupil responses decreases with increasing Rhythmic Complexity. D. Raincloud plots of the evoked pupil dilations by Rhythmic Complexity. The Mid Complexity drumbeat evoked much greater pupil dilations than the Low and High Complexity drumbeats which did not significantly differ from each other. Black diamonds with error bars represent group means with their accompanying standard errors while colored points represent individual subject averages. One outlier was removed for exhibiting dilations nearly four standard deviations smaller than the rest of the sample, although the results did not change in any meaningful way.

EEG Results - Beat frequency neural resonance decreases with increasing complexity

Two participants had to be excluded from the electrophysiological analyses, one because it was corrupted while recording and the other because the recording wasn't saved. Thus, the following analyses report results from 28 rather than all 30 of our subjects. The cluster-based permutation test on the entire analyzed frequency spectrum revealed our expected decrease in intertrial coherence with increasing Rhythmic Complexity, both when the drumbeats were being played to participants ($p < 0.001$) and through the subsequent silence as they imagined it continuing ($p = 0.017$). Unsurprisingly, this corresponded to a frequency range around the beat frequency. At the beat frequency, the cluster test confirmed that there was a significant decrease in intertrial coherence for a cluster containing all electrode sites while the drumbeats were playing ($p < 0.001$) and primarily central electrode locations in the silent entrainment window ($p = 0.007$). These results are displayed in Figure 4 below.

For the electrical activity recorded from the dominant calf, no effect or interaction of Rhythmic Complexity or Electrode were observed in the repeated measures ANOVAs either

while participants were listening to the drumbeats (all p -values > 0.501) or while they imagined them continuing through the silence (all p -values > 0.185).

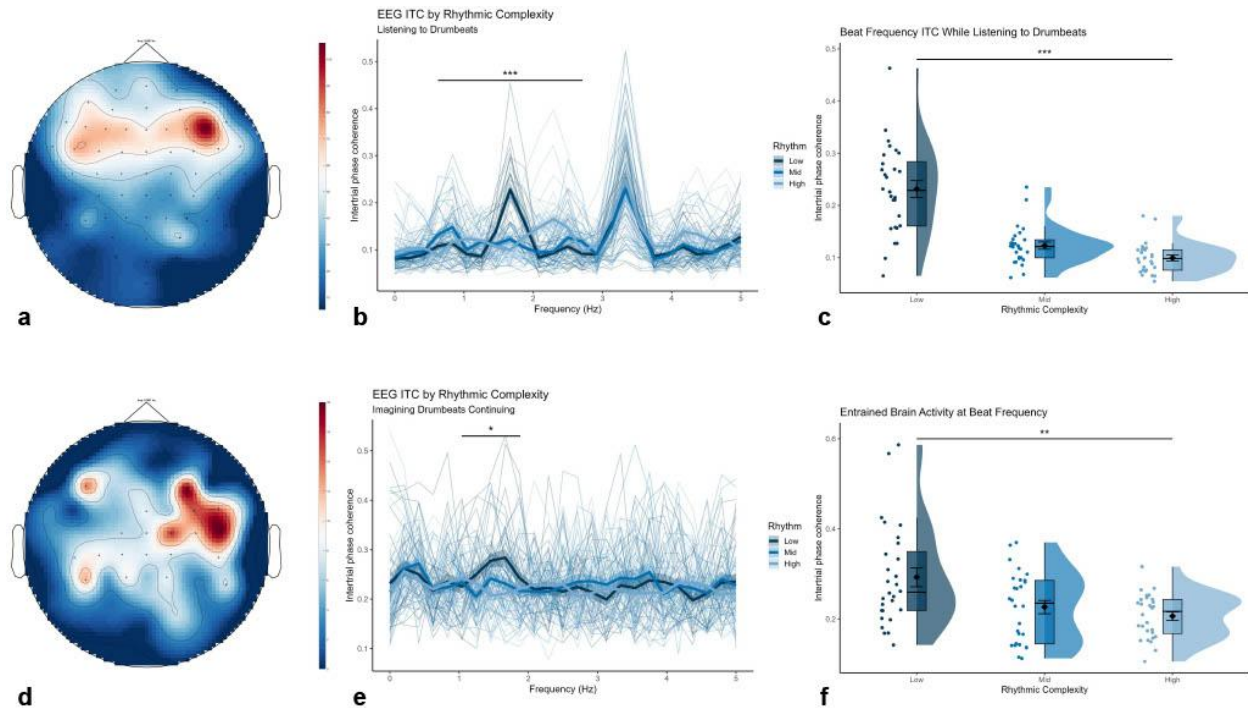


Figure 4. EEG cluster-based permutation test results demonstrating an effect of decreasing ITC with increasing Rhythmic Complexity both while listening to the drumbeats and while imagining them continuing through the silence. The top row corresponds to analyses performed while participants were listening to the drumbeats with **A.** showing the topoplot of the significant cluster at the beat frequency, **B.** showing the ITC at all analyzed frequencies for all subjects, and **C.** showing each participant's ITC at the beat frequency. The bottom row corresponds to analyses performed while participants imagined the drumbeats continuing through the silent window with **D.** showing the topoplot of the significant cluster at the beat frequency, **E.** showing the ITC at all analyzed frequencies for all subjects, and **F.** showing each participant's ITC at the beat frequency. Single asterisks on the topoplots mark electrode sites with $p < 0.01$ significance. Single, double, and triple asterisks in the line and raincloud plots denote significance at $p < 0.001$,

$p < 0.01$, and $p < 0.05$, respectively. Black diamonds with error bars represent group means with their accompanying standard errors while colored points represent individual subject averages.

Discussion

Attention fluctuates over time, dynamically aligning to behaviorally important moments at the optimal point. In this study, we demonstrated that attentional alignment to musical beats worsens with increasing rhythmic complexity as indexed by the ITC of pupillary and EEG activity. This worsening attentional entrainment was observed both while participants were actively listening to musical drumbeats (as shown in the pupillary activity) and persisted through subsequent periods of silence where participants were instructed to merely imagine the drumbeats continuing (as shown in the EEG activity). Moreover, the overall magnitude of sustained pupil dilations was found to correspond to the perceived grooviness of the music. Altogether, these results can be taken as support for theories of dynamic and/or predictive timing in music and groove.

Under DAT, decreasing entrainment in the auditory system leads to worse sensorimotor synchronization and groove is envisioned as embodied neural resonance coding temporal expectations in the premotor cortex (Zalta et al., 2023). Another popular theory, predictive coding (PC), explains these phenomena in different but not incompatible terms: decreasing entrainment represents a decline in the precision of sensory predictions and groove arises as precision-weighted prediction errors stemming from mismatches between sensory predictions and metric expectations (Koelsch et al., 2019; Vuust et al., 2022; Vuust & Witek, 2014). Given the correlational nature of our data, it is possible to view our results in light of either theory; decreasing ITC could reflect worsening entrainment (as envisioned by DAT) or precision of

sensory predictions in the auditory system (as proposed by PC), and sustained pupillary activity could reflect the strength of oscillatory temporal expectations or precision-weighted prediction error under DAT or PC, respectively. DAT, however, is more bottom-up in nature and does not assume the same degree of (if any) top-down prediction hierarchies like PC, leading to arguments that DAT is the more parsimonious account (Palmer & Demos, 2022). On the other hand, PC advocates argue that these top-down predictions are necessary to explain how the same rhythm can be heard in multiple meters, as exemplified in polyrhythms (Vuust et al., 2022). Thus, more work manipulating bottom-up oscillatory processes (e.g., via neurostimulation) and top-down predictions (e.g., via cross-cultural studies) is needed to disentangle which framework better explains beat perception and sensorimotor synchronization.

These results extend past work reporting the pupil's sensitivity to temporal expectations in music (Damsma & Van Rijn, 2017; Fink et al., 2018; Vidal et al., 2023). Using a rather minimal but novel analysis pipeline, we show that pupil dilations predictively align to the beat. While EEG's high temporal resolution has brought criticisms of synchronous activity in the presence of the stimuli because potentially entrained responses can't be distinguished from evoked responses, the pupil dilation response's sluggishness here acts as a strength. Since evoked pupil dilations typically peak on the scale of seconds depending on the task and individual (Denison et al., 2020; Hoeks & Levelt, 1993; McCloy et al., 2016; Wierda et al., 2012), our results likely reflect anticipatory attention allocation to the metrically important moments in the drumbeats. This becomes more plausible considering our analyses were only conducted on timepoints following two full repetitions of the stimulus within each trial so participants had sufficient time to form such metric expectations. As a measure of noradrenergic arousal (Alnæs et al., 2014; Joshi et al., 2016; Murphy et al., 2014), this anticipatory attention could be allocated

as a form of motor preparation which is supported by our sustained pupillary results here as well as previous research on pupil dilations and groove (Bowling et al., 2019; Spiech, Sioros, et al., 2022).

As mentioned in the previous paragraph, oscillatory EEG activity recorded in the presence of oscillatory stimuli cannot distinguish between entrained endogenous oscillators and auditory evoked potentials (Novembre & Iannetti, 2018). Thus, we cautiously interpret our EEG results obtained while the participants listened to the drumbeats as merely evidence that they could perceive the beat prior to imagining it continuing through the silence. It is generally accepted, however, that oscillatory EEG activity recorded from periods of silence *can* index neural entrainment or resonance since there are no auditory stimuli evoking afferent responses (Fujioka et al., 2015; Large, 2008). Indeed, we included silent periods at the end of each trial so that we could measure such entrainment. Despite less statistical power relative to the epochs when the drumbeats were playing, the ITC at the beat frequency continued to exhibit an inverse relationship with rhythmic complexity through the silent window. We therefore interpret this as evidence that as the beat became increasingly obscured by complexity, participants' ability to maintain their perception of the beat diminished.

One potential weakness of our study is that the Mid Complexity drumbeat was only rated higher in groove and liking for the first three blocks of the experiment. It could thus be effectively argued that our results do not reflect the experience of groove. Surely if participants really enjoyed the drumbeats and wanted to move to them, then we likely would have observed more spontaneous movement with the external electrodes placed on the calf muscles, but we did not. These results (or lack of them), however, are unsurprising. Participants likely grew tired of listening to and rating the same three drumbeats over and over again quite quickly; hence,

tapping one's foot or nodding one's head to the beat would seem quite unnatural and uncomfortable, especially while one's head is mounted on a chinrest. For these reasons, we prefer to view our results as expressions of lower level perceptual processes rather than higher order cognitive or motor responses.

In conclusion, we present findings that auditory attention is predictively entrained to metrically relevant moments in music via both oscillatory pupil dilations while listening and endogenous EEG activity through subsequent periods of silence. This entrainment diminishes as the meter becomes further obfuscated with increasing rhythmic complexity. Sustained pupillary activity, as a measure of noradrenergic arousal, is greatest for moderately complex rhythms, perhaps indicating heightened premotor activity or precision-weighted prediction error. In sum, music seems to engage attention in a predictive and dynamic fashion.

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Author contributions

All authors were involved with conceptualization of the study and its experimental design, with the initial idea coming from author CS. Data curation, analysis, and visualization were done by author CS. CS wrote the first draft of the manuscript, while authors AD, BL, and TE revised the manuscript and supervised the entire study.

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Data availability statement

Data for all analyses can be accessed at the following Open Science Framework repository:

https://osf.io/74fxm/?view_only=e03ca5510ece4de2a2773f319c14e436.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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