



The neuro-oscillatory profiles of static and dynamic music-induced visual imagery

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ABSTRACT

Visual imagery, i.e., seeing in the absence of the corresponding retinal input, has been linked to visual and motor processing areas of the brain. Music listening provides an ideal vehicle for exploring the neural correlates of visual imagery because it has been shown to reliably induce a broad variety of content, ranging from abstract shapes to dynamic scenes. Forty-two participants listened with closed eyes to twenty-four excerpts of music, while a 15-channel EEG was recorded, and, after each excerpt, rated the extent to which they experienced static and dynamic visual imagery. Our results show both static and dynamic imagery to be associated with posterior alpha suppression (especially in lower alpha) early in the onset of music listening, while static imagery was associated with an additional alpha enhancement later in the listening experience. With regard to the beta band, our results demonstrate beta enhancement to static imagery, but first beta suppression before enhancement in response to dynamic imagery. We also observed a positive association, early in the listening experience, between gamma power and dynamic imagery ratings that was not present for static imagery ratings. Finally, we offer evidence that musical training may selectively drive effects found with respect to static and dynamic imagery and alpha, beta, and gamma band oscillations. Taken together, our results show the promise of using music listening as an effective stimulus for examining the neural correlates of visual imagery and its contents. Our study also highlights the relevance of future work seeking to study the temporal dynamics of music-induced visual imagery.

1. Introduction

Visual imagery refers to the representation of visual mental images in the absence of corresponding visual input from the external world (Kosslyn, 1975; Kosslyn et al., 2006). It has been shown to be highly prevalent during music listening (Dahl et al., 2022; Hashim et al., 2023; Küssner and Eerola, 2019; Vuoskoski and Eerola, 2015) and to play a key role in both music's aesthetic appeal (Belfi, 2019) and emotional power (Balteş and Miu, 2014; Hashim et al., 2020; Juslin, 2013; Juslin and Västfjäll, 2008; see also, Taruffi and Küssner, 2019, 2022). There is evidence that the content of music-induced visual imagery can take a variety of forms: content analyses have revealed that they can manifest as concrete or abstract concepts (Küssner and Eerola, 2019), and other exploratory investigations suggest that significant amounts of imagery are formulated as narratives or story-like sequences (Dahl et al., 2022; Hashim et al., 2023; Margulis, 2017). However, despite the relevance of

such an endeavour, there have been very few attempts to use music to examine the neural signatures of visual imagery and to explore how these signatures may vary as a function of imagery content.

1.1. Neural correlates of visual imagery

It is well documented that visual imagery involves similar neural substrates to those implicated in visual perception (Cichy et al., 2012; Dijkstra et al., 2019; Lee et al., 2012; Mutha et al., 2014; Schaefer et al., 2013; Xie et al., 2020; Zacks, 2008). Indeed, while early studies tended to emphasize the role of alpha oscillations (Salenius et al., 1995; Williamson et al., 1997; Xie et al., 2020) and posterior brain regions (Drever, 1955; Gale et al., 1972; Kaufman et al., 1990; Williamson et al., 1997) in visual imagery, it is increasingly clear that, as for visual perception, visual imagery of complex content may implicate a wide range of oscillatory frequency bands and brain areas.

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For instance, in addition to the electroencephalography (EEG) studies emphasising *suppression* of occipital alpha (indicating increased neural firing in visual areas) as a signature of visual imagery formation, enhanced gamma power in the occipital brain region has also been associated with the experience of creative and vivid spontaneous visual imagery (Luft et al., 2019), the content-specific features of visual imagery (Lehmann et al., 2001), and with working memory load during motor imagery (De Lange et al., 2008; Sepúlveda et al., 2014). Similarly, theta and beta oscillations have (along with alpha) been shown to be successful in discriminating the contents of visual imagination (Xie et al., 2020), while lower [8–10 Hz] and upper [11–13 Hz] bands of alpha appear to show nuances in terms of how they relate to visual imagery formation (Gualberto Cremades, 2002; Petsche et al., 1997).

With regard to implicated areas, a large body of studies has shown that (in addition to posterior areas) parietal, central, and frontal areas of the brain are also involved in visual imagery, particularly in the context of spatial and motor aspects (de Borst et al., 2012; Menicucci et al., 2020; Mutha et al., 2014; Sousa et al., 2017; Thompson et al., 2009; Villena-González et al., 2018; Zabielska-Mendyk et al., 2018; Zacks, 2008). For instance, it has been suggested that frontal regions may be essential for integrating the “what” and “where” contents of visual thought, that are processed by occipitotemporal and parietal areas respectively (de Borst et al., 2012). Further, in a meta-analysis seeking to clarify what, if any, shared components exist for kinaesthetic and visual imagery in the context of sports (Filgueiras et al., 2018), it was shown that athletes' visual motor imagery (i.e., visualizing a movement execution) of sports actions was similar to their kinaesthetic motor imagery (i.e., imagining the sensations of the movement execution) in recruiting, amongst others, frontal motor (including premotor and supplementary motor areas) and parietal areas involved in feeling their own movements (somatosensory cortex, inferior and superior parietal lobule).

1.2. Comparing electrophysiological correlates of static and dynamic visual imagery

Given evidence that motoric aspects of visual imagery may implicate additional brain areas, an interesting question is how the electrophysiological correlates of static and dynamic forms of visual imagery compare. In one EEG study testing the possibility that pure visual motion imagery can be used as a tool for brain computer interfacing (Sousa et al., 2017), participants were asked to imagine a dot in three modes: static, moving in two opposing directions, and moving in four opposing directions. Compared to observing a static dot on a screen, observing a moving dot led to a greater decrease of alpha levels in posterior brain areas (parietal, parieto-occipital, and occipital areas) supporting the role of visual cortices in visual imagery. However, imagery of the moving dots (compared to the static dot) was also characterised by greater alpha in frontal as well as a decrease of beta activity in fronto-central channels. The authors accounted for their findings of increased frontal alpha to visual motion imagery (compared to static imagery) on the basis of frontal alpha's purported role in tasks with high internal processing demands (e.g., working memory and creative thinking), and based on the association of frontal alpha with reduced external processing and increased task complexity (Cooper et al., 2003; Klimesch et al., 2007; Sauseng et al., 2005; Schomer and da Silva, 2012).

Other studies have reported and interpreted beta band involvement in visual imagery even though no solid conclusions have been drawn. Villena-González et al. (2018) found an enhancement of beta power during a task where participants attended to a series of beep tones, following an instruction to visually imagine anything they wanted. They suggested that the presence of beta band activity may indicate the cross-modal processing of the visual imagery and auditory task. In contrast, beta power suppression has been associated with imagination of complex movement in a number of studies (e.g., Zabielska-Mendyk et al., 2018; Menicucci et al., 2020). In the study by Menicucci et al. (2020),

parallels were reported between the profiles of beta and alpha band amplitude, with greater beta suppression in fronto-central and centro-parietal areas (along with alpha suppression in fronto-central areas) during a visual motor imagery task. Here, it is also relevant to note studies that emphasize a rebound of beta power – suppression followed by enhancement – after both real and imagined movements (Neuper and Pfurtscheller, 1996; Salmelin et al., 1995). Indeed, one possibility is that both beta suppression and enhancement effects may be expected in dynamic imagery depending on whether motor-associated imagery is being or, conversely, has just been experienced.

In sum, research to date suggests that while visual imagery involves visual cortices, particularly with respect to suppression of alpha activity, incorporating complex features such as motion may engage additional motoric processes in other areas of the brain (for a meta-analysis of the neural correlates of motor imagery, see also Hardwick et al., 2018). In other words, research corroborates the idea that static and dynamic visual imagery experiences may be neurally dissociable. Here we suggest that music, with its capacity for inducing both static and dynamic forms of visual imagery, may be a useful stimulus for throwing light on this hard-to-grasp phenomenon.

1.3. Music-induced static and dynamic visual imagery

As previously mentioned, visual imagery is a common experience during music listening (Küssner and Eerola, 2019; Vuoskoski and Eerola, 2015) with the average latency of music-induced visual imagery reported as being about 12 s after music onset (Day and Thompson, 2019), and with music-induced imagery evidenced to have a wide breadth of content (Küssner and Eerola, 2019; Taruffi and Küssner, 2019; Vuoskoski and Eerola, 2015).

Indeed, studies requiring participants to describe details of their music-induced visual imagery experiences have shown how visual imagery can incorporate motoric aspects. For instance, in one recent study by Dahl et al. (2022), a content analysis of music-induced visual imagery descriptions showed that *Movement and Events* was a prominent category of listeners' experience. Similarly, Küssner and Eerola (2019) reported on how visual imagery can vary from static scenes to fast changing storylines, while other work has cited dynamic forms of imagery in association with perceived motion and metaphor in musical contexts (Eitan and Granot, 2006; Johnson and Larson, 2003). Within this literature on the cross-modal experience of music, Zhou et al. (2015), for instance, showed that music can express a sense of movement as a function of acoustic parameters such as pitch range and intensity. Further, other authors have emphasized that contours in melodic lines and forces evoked by changes in tempo are what may drive mental imagery of movement (Eitan and Granot, 2006).

However, despite the relevance of using music listening as a vehicle to study the neural correlates of the content of visual imagery (for a general overview of neuroscientific measures of music and mental imagery, see Belfi, 2022), only one such study exists: Fachner et al. (2019) recorded EEG during a guided imagery and music (GIM) session – where GIM involves the induction of visual imagery in response to a specialised GIM soundtrack – from both a therapist and client simultaneously. Comparing moments of interest (characterised by imagery) to moments of non-interest, they found greater posterior alpha suppression during moments of visual imagery formation.

The findings from Fachner and colleagues are promising because they are in line with previous work on visual imagery. However, as that study examined only one participant and as it focused primarily on examining power in the alpha band, it is clear that further work is needed. Indeed, while it is likely that visual imagery to music activates largely similar brain areas as visual imagery to non-music-related stimuli, and while there is preliminary evidence that occipital alpha suppression should be a key signature of interest, it seems relevant to ask whether different forms of music-induced visual imagery – here, static versus dynamic imagery – may be reflected by different neural patterns.

1.4. The current research

The current study aimed to throw light on the extent to which static and dynamic music-induced visual imagery may be associated with differing neural patterns with respect to three regions of interests (frontal, centro-parietal, and parieto-occipital) and three frequency bands of interest (alpha [8–13 Hz], beta [14–30 Hz], and gamma [30–45 Hz]). Based on evidence that visual imagery tends to occur within the first 12 s of listening (Day and Thompson, 2019) and in light of evidence that contrasting effects may occur within the same oscillatory frequency bands (e.g., as a function of whether imagery is ongoing or recently completed; Neuper and Pfurtscheller, 1996), we also explored how imagery-related neural activity differed in key phases of the listening experience (the first and second halves of the piece).

Participants were instructed to listen, with closed eyes and while EEG was recorded, to twenty-four excerpts of music that had been shown in a previous study to induce joyful, neutral or fearful emotions in the listener (Koelsch et al., 2013). After each excerpt, they rated – on a continuous scale – the amount of static and dynamic visual imagery experienced in response to the music. In line with previous research, in general (Cooper et al., 2003; Drever, 1955; Gale et al., 1972; Salenius et al., 1995; Williamson et al., 1997; Xie et al., 2020) and in the context of music listening (Fachner et al., 2019), we expected to see a negative relationship between the amount of music-induced visual imagery reported and alpha band activity particularly in the parieto-occipital area of the brain, reflecting enhanced neural firing in visual areas during imagery.

Critically, we also predicted, in line with past findings regarding beta activity during motor and visual-motor processing (Menicucci et al., 2020; Zabielska-Mendyk et al., 2018), that dynamic imagery may involve both beta suppression (desynchronisation) and enhancement (due to rebound effects), where suppression reflects motor processing, and enhancement reflects (a) a rebound of beta power following such processing (Neuper and Pfurtscheller, 1996), and (b) the potential cross-modal processing of visual imagery and the auditory listening task (Villena-González et al., 2018). Finally, we predicted we would find parieto-occipital gamma enhancement, reflecting increased neural firing, in response to visual imagery generally (in line with previous results examining vivid spontaneous visual imagery in single case studies, Lehmann et al., 2001; Luft et al., 2019), but potentially in response to dynamic imagery more specifically (in line with past relationships found between motor imagery tasks and gamma enhancement, De Lange et al., 2008; Sepúlveda et al., 2014).

2. Methods

2.1. Participants

Forty-three participants took part in the experiment. One participant was excluded due to extreme values that could not be accounted for. This resulted in forty-two participants (27 female, 15 male; Age $M = 28.85$, $SD = 4.85$; note that age data was missing from one participant) being included in the analyses. About 95 % (40 of 42) of participants reported no hearing issues. One participant mentioned having a hearing aid or implant (i.e., corrected hearing that should not pose any issues for the data), and the final participant provided no response but reported that the musical selection was pleasant and varied and that they listened to all musical stimuli ‘pretty attentively’. Thus, these two participants were retained for further analyses.

Ethical approval (Ref. 2017-32) for the research was granted by the Ethics Committee of the Institute of Psychology at Humboldt-Universität zu Berlin, Germany. All participants provided written consent to be included and were given monetary compensation or course credit for their time.

2.2. Materials

Twenty-four musical excerpts that had been shown to induce joyful, fearful, and neutral emotions were chosen (eight excerpts per emotion) for the listening task. They were obtained from a set of stimuli used in a previous study by Koelsch et al. (2013).

The joyful excerpts consisted of CD-recorded pieces derived from a variety of musical styles and genres (classical, South American and Balkan music, Irish jigs, jazz, reggae). The fearful excerpts were obtained from soundtracks of suspense movies and video games. Their fearful qualities were further enhanced by creating two copies from each original excerpt: one copy pitch-shifted a semitone upwards and the other shifted a tritone downwards. The original excerpt and both copies were merged into a single wav file. The neutral excerpts comprised sequences of isochronous tones selected at random from a pentatonic scale, which were set using high quality natural instrument libraries from Ableton (<https://www.ableton.com/en/>) to ensure ecological validity.

The 7-item Musical Training subscale of the Goldsmiths Musical Sophistication Index (Gold-MSI; Müllensiefen et al., 2014) was included to gauge prior training in music. Examples of items include ‘I spend a lot of my free time doing music-related activities’ and ‘I would not consider myself a musician’. Each item was rated on a 7-point Likert scale.

2.3. Procedure

The experiment consisted of two main 28-trial counterbalanced blocks, consisting of 4 practice trials and 24 experimental trials. In one block, participants provided self-report ratings related to visual imagery (analysed here and discussed exclusively henceforth), and in the other, they provided ratings regarding emotion-related experiences, which will be analysed and discussed elsewhere. In both blocks, participants were presented with the same set of twenty-four excerpts (i.e., two repetitions of the musical stimuli). Note that while this means that half of our participants (who were presented with the visual imagery block second in the counterbalancing order) provided their imagery ratings in a second round of listening to the stimuli, this should not affect the conclusions we seek to draw with this study.

Each main block took approximately 25 mins to complete. During the experimental trials, participants listened to the 24 30-s musical excerpts aloud from two speakers set to a volume they found comfortable and, after each excerpt, were instructed to rate their static and dynamic visual imagery experience (‘As soon as the piece of music has finished, please open your eyes and rate how strongly it evoked still and moving images in your mind’s eye’) using a visual analogue scale from 0 to 100. Participants always rated their static imagery experience first, followed by their dynamic imagery experience. The static imagery rating ranged from 0 = ‘Did not trigger any still images in me at all’ to 100 = ‘Triggered a lot of still images in me’ (translated from German, see Table S1 for the original anchor points used). The dynamic imagery rating ranged from 0 = ‘Did not trigger any moving images in me at all’ to 100 = ‘Triggered a lot of moving images in me’ (translated from German).

Participants were instructed at the beginning of each block that they should keep their eyes closed for the duration of each music excerpt to promote concentration and introspection and that they would be alerted as to when to close their eyes again after providing their ratings on a previous trial (‘So that you can always close your eyes in time, a visual countdown will appear before each piece of music, announcing the beginning of the respective piece of music’). Once ratings were provided (no time limit was given for providing ratings), a 4-s visual countdown (a short horizontal line that decreased in length with each second to become a dot at music onset) announced the start of the next listening trial. See Fig. 1 for a summary of the trial procedure.

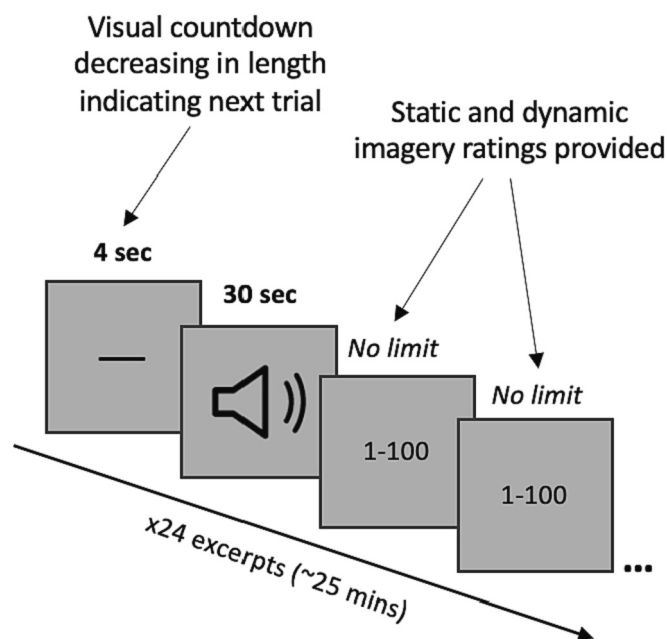


Fig. 1. Procedure summary of each trial.

2.4. EEG recording

EEG was recorded using sintered Ag/AgCl active electrodes (suitable for reducing noise by amplifying the signal close to the source) and two 16-channel USB biosignal amplifiers (g.USBamp, g.tec medical engineering GmbH, Austria). A 530 Hz antialiasing filter was applied during recording, and the EEG recording sampling rate was set to 1200 Hz. A 15-channel 10–20 system cap was used, consisting of the following electrodes: AF3, AF4, F3, Fz, F4, C3, Cz, C4, P3, Pz, P4, POz, PO7, Oz, and PO8. The reference channel was placed on the right mastoid, and the ground electrode was placed on the atlas (i.e., the top of the spine/back of the neck). For re-referencing offline to a non-lateralized reference, an additional electrode was placed on the left mastoid. Electrode impedance was maintained beneath 10 k Ω .

2.5. EEG data analyses

The EEG data was imported into MATLAB using EEGLAB (Delorme and Makeig, 2004) functions and pre-processed using the FieldTrip toolbox (Oostenveld et al., 2011). The data was downsampled to a sampling rate of 200 Hz and filtered using a low-pass filter at 50 Hz. The data was subsequently segmented into epochs of 32 s, which comprised a 2-s pre-trial baseline phase and a 30-s main trial phase. All data was re-referenced to the average activity of the right and left mastoid channels.

The data (1,008 trials: 42 participants, 24 visual imagery main trials per participant, excluding practice trials) was visually assessed for artefacts. This allowed identification of channels that were faulty or that displayed extreme levels of variance. Across all participants, rejected channels (on average 1.7 and no more than four per participant) were interpolated with the average of neighbouring channels. Next, an independent component analysis (ICA) using the Runica algorithm (which implements the logistic infomax algorithm from EEGLAB; Delorme and Makeig, 2004) was run. Spatial topographies were plotted, and individual components that were visually identified as eye movements, eye blinks, or localised electrode activity were noted and rejected from the data (on average 1.24 components per participant removed).

A Fast Fourier Transform frequency decomposition was carried out using a Hanning taper, with power computed in 1-s non-overlapping segments. Frequencies were extracted between 8 and 13 Hz for alpha band, between 14 and 30 Hz for beta band, and between 30 and 45 Hz

for gamma band. For exploratory analyses, the alpha band was further subdivided into lower [8–10 Hz] and upper alpha [11–13 Hz]. The oscillatory power was baseline-corrected by subtracting the mean power of the 2-s pre-stimulus interval, separately for each trial within each channel. Specifically, for each trial within each channel, the average power in the prior two seconds (baseline period) was subtracted from power in each 1-s segment of the 30-s main trial.

2.6. Statistical analyses

Our primary aim was to examine the relationship between visual imagery ratings (static and dynamic) and different forms of oscillatory activity (alpha, beta, and gamma power), and to determine how these relationships differed as a function of brain areas and time period. To this end, EEG channels were grouped into three regions of interest (ROI): Frontal (AF3, AF3, F3, Fz, and F4), Centro-Parietal (C3, Cz, C4, P3, Pz, and P4), and Parieto-Occipital (POz, PO7, Oz, and PO8), and the 30-s time windows of the main trials were divided into two phases: the First Half, comprising the first 15 s of a trial, and the Second Half, comprising the final 15 s of a trial. Here it is important to note that due to only having a single static and dynamic imagery rating for the whole trial (rather than continuous imagery ratings over time), our consideration of time effects are necessarily on a macro-level and are largely motivated by the finding that music-induced visual imagery occurs on average around 12 s after music onset (Day and Thompson, 2019). Given that this estimation of imagery onset lies within the first half of our musical trials and given that dynamic imagery may nevertheless be expected to continue to change over time relative to static imagery, it seemed relevant to ask how patterns of activity in the first and second halves of our trials differed for the two types of imagery.

All statistical analyses were carried out using R (Version 4.2.3; R Core Team, 2018) and linear mixed models were estimated using the *lme4* (Bates et al., 2015) and *lmerTest* (Kuznetsova et al., 2017) R packages, the latter of which provided the *t* and *p*-values for our models. Given our main aim (to observe how static and dynamic ratings influenced oscillatory power differently as a function of brain areas and time period), we estimated, for each frequency band, a restricted maximum likelihood linear mixed model with oscillatory power as dependent variable, and static and dynamic imagery, and the interactions between each of these rating types with time period (First Half and Second Half) and ROI (Frontal, Centro-Parietal, and Parieto-Occipital), as fixed effects. Random effects were an intercept for participant and a nested random intercept between musical excerpt and excerpt type (joyful, neutral, fearful). Where this extra dimension in the random effects led to failed convergence in models, random effects were simplified by excluding the nested intercept and retaining only participant and excerpt type as random effects.

A Pearson's correlation coefficient showed static and dynamic imagery to correlate negatively but very weakly with each other, $r(1,006) = -0.094$, $p = 0.003$. We included both ratings within the same models to allow us to observe the potentially different influences of each on the dependent variable.

See Table S2 for a full summary of all omnibus models across all our frequency bands of interest. Follow-up models were run to explore any significant interactions emerging from the above models for each frequency band.

In an additional set of exploratory analyses, we analysed the influence of musical training on the pattern of EEG findings. To this end, musical training was dichotomised into high and low scores using a median split. Once again, we estimated for each frequency band a linear mixed model with oscillatory power as dependent variable, and as fixed effects: static and dynamic imagery, and interactions between these and musical training (High and Low) and time period. Random effects in each model were an intercept for participant and a nested random intercept between musical excerpt and excerpt type (joyful, neutral, fearful).

3. Results

3.1. Analysis of alpha power

The overall model predicting alpha band showed main effects of static, $F(1, 435,460) = 4.89, p = 0.027$, and dynamic imagery, $F(1, 728) = 21.79, p < 0.001$, whereby high ratings were associated with suppression in alpha (see Table 1 for means and standard deviations of the two rating types), a main effect of time period, $F(1, 453,518) = 151.35, p < 0.001$, whereby there was less alpha power in the second compared to the first half of the trial, and also a main effect of ROI, $F(2, 453,518) = 295.10, p < 0.001$, whereby there was less alpha power in the frontal area, followed by the parieto-occipital area, then the centro-parietal area (see Table 2 and Fig. 2 for means and standard deviations of oscillatory power for the three frequency bands across the two time periods and three regions of interest. Also see Fig. S1 for a frequency power plot displaying power across all trials and all frequency bands).

There were also interactions found between static imagery and time period, $F(1, 453,518) = 32.62, p < 0.001$, and between dynamic imagery and time period, $F(1, 453,518) = 38.28, p < 0.001$. To explore the significant interactions between static imagery and time period, a model was run to examine the relationship between static imagery ratings and alpha power for each time period separately. As also illustrated in Fig. 3A and C, these revealed a significant negative association between alpha and static imagery (i.e., higher ratings in static imagery were associated with reduced alpha power) in the first half of the trial, $\beta = -0.00189, SE = 0.00134, t(1.61) = -3.65, p < 0.001$, but a significant positive relationship in the second half, $\beta = 0.00328, SE = 0.00128, t(2.10) = 2.57, p = 0.010$. Similarly, to explore the significant interaction between dynamic imagery and time period, a model was once more run for each time period separately. These revealed that dynamic imagery ratings' negative relationship with alpha power was significant in the first half, $\beta = -0.00550, SE = 0.00129, t(1290.48) = -4.27, p < 0.001$, but non-significant in the second half, $\beta = -0.00040, SE = 0.00123, t(2.56) = -0.32, p = 0.746$.

There was a significant interaction between ROI and both static, $F(2, 453,518) = 33.10, p < 0.001$, and dynamic imagery, $F(2, 453,518) = 121.88, p < 0.001$. To explore the significant interaction between static imagery and ROI, a model examining the relationship between power and ratings was run for each ROI separately. While no significant effects were found with respect to the frontal, $\beta = -0.00098, SE = 0.00080, t(1.41) = -1.23, p = 0.218$, centro-parietal, $\beta = -0.00008, SE = 0.00161, t(1.51) = -0.05, p = 0.961$, or parieto-occipital areas, $\beta = 0.00092, SE = 0.00209, t(9.04) = -0.440, p = 0.660$, the interaction likely reflected a tendency for the relationship to be more systematically negative in frontal areas than in the other two ROIs (see also Fig. 3B). Finally, following up the significant interaction between dynamic imagery and ROI, it was revealed that, as for static imagery, there was a tendency for the relationship to be more negative in frontal and posterior areas; specifically, while dynamic imagery ratings were significantly negatively linked to frontal alpha, $\beta = -0.00267, SE = 0.00076, t(1.38) = -3.49, p < 0.001$, and parieto-occipital alpha, $\beta = -0.00441, SE = 0.00199, t(956.51) = -2.22, p = 0.027$, there was no significant effect for the centro-parietal area, $\beta = -0.00106, SE = 0.00121, t(1.81) =$

Table 1

Summarising the descriptive statistics of static and dynamic visual imagery across the three types of musical excerpts presented to participants (joyful, neutral, and fearful).

	Mean rating (standard deviation)			
	Joyful	Neutral	Fearful	Overall
Static imagery	28.26 (22.98)	34.75 (29.25)	30.10 (22.65)	31.04 (25.29)
Dynamic imagery	68.66 (24.91)	26.43 (24.92)	51.90 (27.85)	49.00 (31.21)

Table 2

Summarising the descriptive statistics of the frequency bands of interest across the two time periods (First Half and Second Half) and the three regions of interest (ROI; Frontal, Centro-Parietal, and Parieto-Occipital).

	Mean power (standard deviation)				
	Time period		ROI		
	First half	Second half	Frontal	Centro-parietal	Parieto-occipital
Alpha	-4.08 (32.84)	-4.52 (32.55)	-5.14 (30.85)	-3.59 (33.17)	-4.30 (34.15)
Beta	-0.99 (7.18)	-1.05 (6.64)	-1.09 (5.17)	-0.97 (7.25)	-1.01 (8.20)
Gamma	-0.62 (1.81)	-0.64 (2.16)	-0.74 (2.51)	-0.59 (1.92)	-0.55 (1.23)

$-0.87, p = 0.383$.

Finally, there was a significant interaction between ROI and time period, $F(2, 431,941) = 8.01, p < 0.001$. However, this was not explored further due to the current investigation's focus on visual imagery effects. No other main effects or interactions were significant.

3.2. Analysis of beta power

The overall model for beta band showed a significant main effect of static imagery, $F(1, 453,488) = 176.64, p < 0.001$, and of dynamic imagery, $F(1, 281,826) = 9.50, p = 0.002$. High static imagery ratings were associated with higher beta power, whereas high dynamic imagery ratings were associated with lower beta power. There was also a main effect of time period, $F(1, 453,518) = 9.92, p = 0.002$, whereby there was higher beta power in the first half than in the second, as well as a main effect of ROI, $F(2, 453,518) = 22.69, p < 0.001$, showing there to be less beta power in the frontal area, followed by parieto-occipital, then the centro-parietal area.

There was also a significant interaction between static imagery and time period, $F(1, 453,518) = 90.52, p < 0.001$, and between dynamic imagery and time period, $F(1, 453,518) = 99.62, p < 0.001$. To explore the significant interactions between time period and both static and dynamic imagery, we ran four follow-up models. These showed a significant positive relationship between static ratings and beta power in the first time period, $\beta = 0.01193, SE = 0.00065, t(2.26) = 18.39, p < 0.001$, but no significant relationship in the second, $\beta = 0.00085, SE = 0.00059, t(2.27) = 1.44, p = 0.150$. In contrast, dynamic imagery had a significant negative relationship with beta power in the first time period, $\beta = -0.00674, SE = 0.00063, t(7.55) = -10.70, p < 0.001$, and a significant positive relationship in the second time period, $\beta = 0.00133, SE = 0.00058, t(1.54) = 2.31, p = 0.021$. See Fig. 4A and C which visualise beta power against dynamic imagery ratings across the two time periods.

Further, there was a significant interaction between static imagery and ROI, $F(2, 453,518) = 6.67, p = 0.001$. Exploration of the significant interaction between static imagery and ROI revealed significant positive relationships between static imagery and beta power in all the ROIs that nevertheless decreased in size from the front to the back of the head (frontal area, $\beta = 0.00642, SE = 0.00048, t(1.51) = 13.31, p < 0.001$; centro-parietal area, $\beta = 0.00623, SE = 0.00074, t(1.80) = 8.42, p < 0.001$; parieto-occipital area, $\beta = 0.00657, SE = 0.00104, t(1.21) = 6.30, p < 0.001$).

There was further a significant interaction between dynamic imagery and ROI, $F(2, 453,518) = 7.17, p < 0.001$, as well as a significant three-way interaction between dynamic imagery, time period, and ROI, $F(2, 453,518) = 9.19, p < 0.001$. We summarise the latter interaction as it provides an extra dimension of detail. Exploration of this three-way interaction revealed a significant negative relationship between dynamic imagery and beta power in the frontal area in the first half, $\beta = -0.00612, SE = 0.00052, t(3.91) = -11.74, p < 0.001$, but a non-

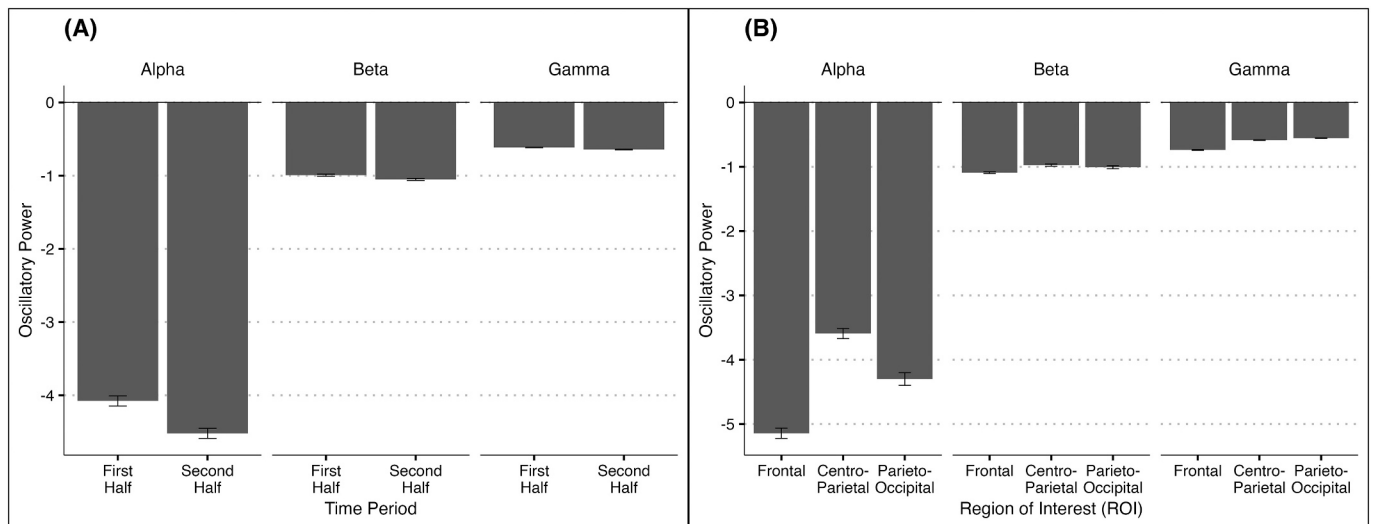


Fig. 2. Illustrating oscillatory power across the three frequency bands (alpha, beta, and gamma), including error bars depicting \pm standard error of the mean. (A) Average power across the two time periods (First Half and Second Half). (B) Average power across the three regions of interest (ROI; Frontal, Centro-Parietal, and Parieto-Occipital).

significant negative relationship in the second half, $\beta = 0.00043$, $SE = 0.00078$, $t(4.40) = -0.55$, $p = 0.581$. Further, there was a significant negative relationship between dynamic imagery and beta power in the centro-parietal area in the first half, $\beta = -0.00494$, $SE = 0.00105$, $t(4.52) = -4.72$, $p < 0.001$, but a non-significant positive relationship in the second half, $\beta = 0.00152$, $SE = 0.00098$, $t(3.45) = 1.55$, $p = 0.120$. Finally, there was also a significant negative relationship between dynamic imagery and beta power in the parieto-occipital area in the first half, $\beta = -0.01031$, $SE = 0.00161$, $t(1.92) = -6.41$, $p < 0.001$, as well as significant positive relationship in the second half, $\beta = 0.00305$, $SE = 0.00121$, $t(3.63) = 2.52$, $p = 0.012$. No other main effects or interactions were significant.

Finally, there was a significant interaction between ROI and time period, $F(2, 453,518) = 3.59$, $p = 0.027$. However, again, this was not explored due to the current investigation's focus on visual imagery effects. No other main effects or interactions were significant. See also Fig. 4B which visualises beta power against static and dynamic imagery ratings across regions of interest.

3.3. Analysis of gamma power

The overall model predicting gamma band revealed a significant main effect of dynamic imagery, $F(1, 14,847) = 5.73$, $p = 0.017$, whereby an increase in dynamic imagery ratings was related to an enhancement of gamma power, as well as a significant main effect of ROI $F(2, 453,518) = 475.81$, $p < 0.001$. There was also a significant interaction between dynamic imagery ratings and time period, $F(1, 453,518) = 14.89$, $p < 0.001$. To examine the interaction between dynamic imagery ratings and time period, a model was run for each time period separately. Dynamic imagery ratings showed a significant positive relationship with gamma power in the first time period, $\beta = 0.00038$, $SE = 0.00011$, $t(2.04) = 3.34$, $p < 0.001$, but no effect in the second half, $\beta = -0.00007$, $SE = 0.00016$, $t(5.55) = -0.42$, $p = 0.673$. See Fig. 5A and C which visualise gamma power against static and dynamic imagery ratings across the two time periods.

There was a significant interaction between static imagery ratings and ROI, $F(2, 453,518) = 222.20$, $p < 0.001$, and between dynamic imagery and ROI, $F(2, 453,518) = 24.45$, $p < 0.001$. Following up the interaction between static imagery and ROI revealed non-significant positive relationships between static imagery ratings and gamma in all three ROIs but indicated that these positive relationships were stronger in the centre than in the front and back of the head (frontal area, $\beta =$

0.00011 , $SE = 0.00019$, $t(1.41) = 0.59$, $p = 0.554$; centro-parietal area, $\beta = 0.00026$, $SE = 0.00015$, $t(1.76) = 1.72$, $p = 0.085$; parieto-occipital area, $\beta = 0.00002$, $SE = 0.00012$, $t(1.17) = 0.15$, $p = 0.883$). Finally, following up the interaction between dynamic imagery ratings and ROI revealed a significant relationship in the centro-parietal area only, showing that effects generally became more enhanced in the centre of the head than in the front and back (frontal area, $\beta = 0.00004$, $SE = 0.00018$, $t(1.67) = 0.22$, $p = 0.826$; centro-parietal area, $\beta = 0.00036$, $SE = 0.00015$, $t(5.35) = 2.44$, $p = 0.015$; parieto-occipital area, $\beta = 0.000002$, $SE = 0.00011$, $t(3.10) = 0.02$, $p = 0.982$). See also Fig. 5B which visualises gamma power against static and dynamic imagery ratings across regions of interest. No other main effects or interactions were significant.

3.4. Exploratory analyses: lower and upper alpha

Current evidence is mixed regarding a potentially nuanced role of upper and lower alpha in visual imagery: for example, while Petsche et al. (1997) linked visual imagination to greater power suppression in upper (than lower) alpha, Gualberto Cremades (2002) suggested that there is greater attenuation of lower (than upper) alpha particularly in those imagery tasks for which high attention and arousal is required.

In a set of exploratory analyses, we therefore examined how upper and lower alpha differ in their relationship to visual imagery by estimating the same modelling analysis (as carried out for alpha, beta, and gamma bands) for lower and upper alpha bands separately (see Supplementary Materials for a detailed outline of the results, and see Table S3 and Fig. S2 for means and standard deviations of lower and upper alpha power across the two time periods and three regions of interest).

Analysis of lower alpha showed a pattern of results that was almost identical to that seen for the full alpha band. Significant suppression in the low alpha frequencies was found more clearly in the first half of a trial than in the second half in response to both static and dynamic imagery. Additionally, trends towards suppression in the low alpha frequencies in all ROIs in response to high static and dynamic imagery were found, in addition to a significant suppression of frontal lower alpha power in response to dynamic imagery. In contrast, analysis of the upper alpha band, while largely similar to overall alpha, failed to show the strength of static imagery-related alpha suppression that was seen in lower alpha.

Further, while suppression in the frontal area associated with

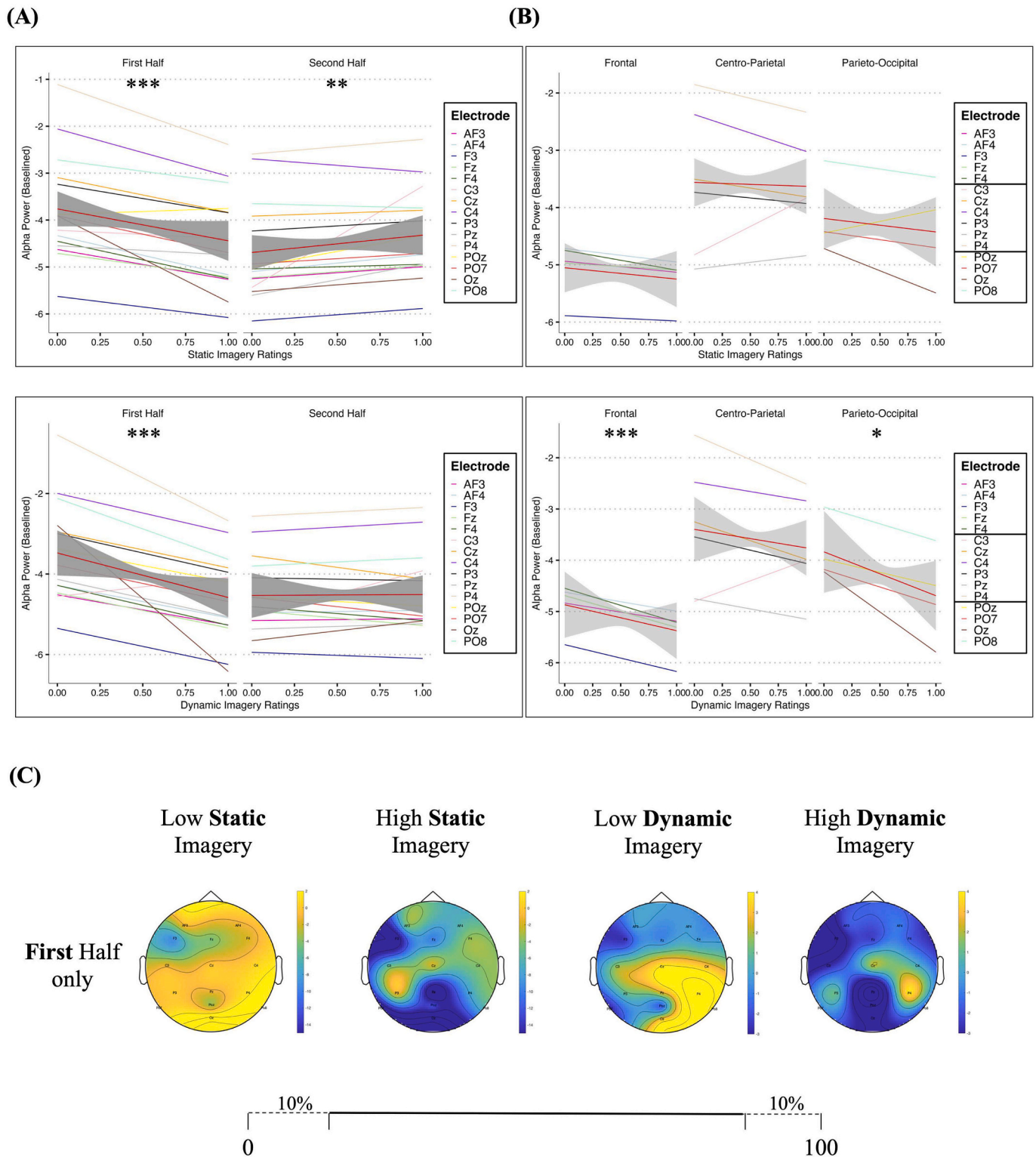
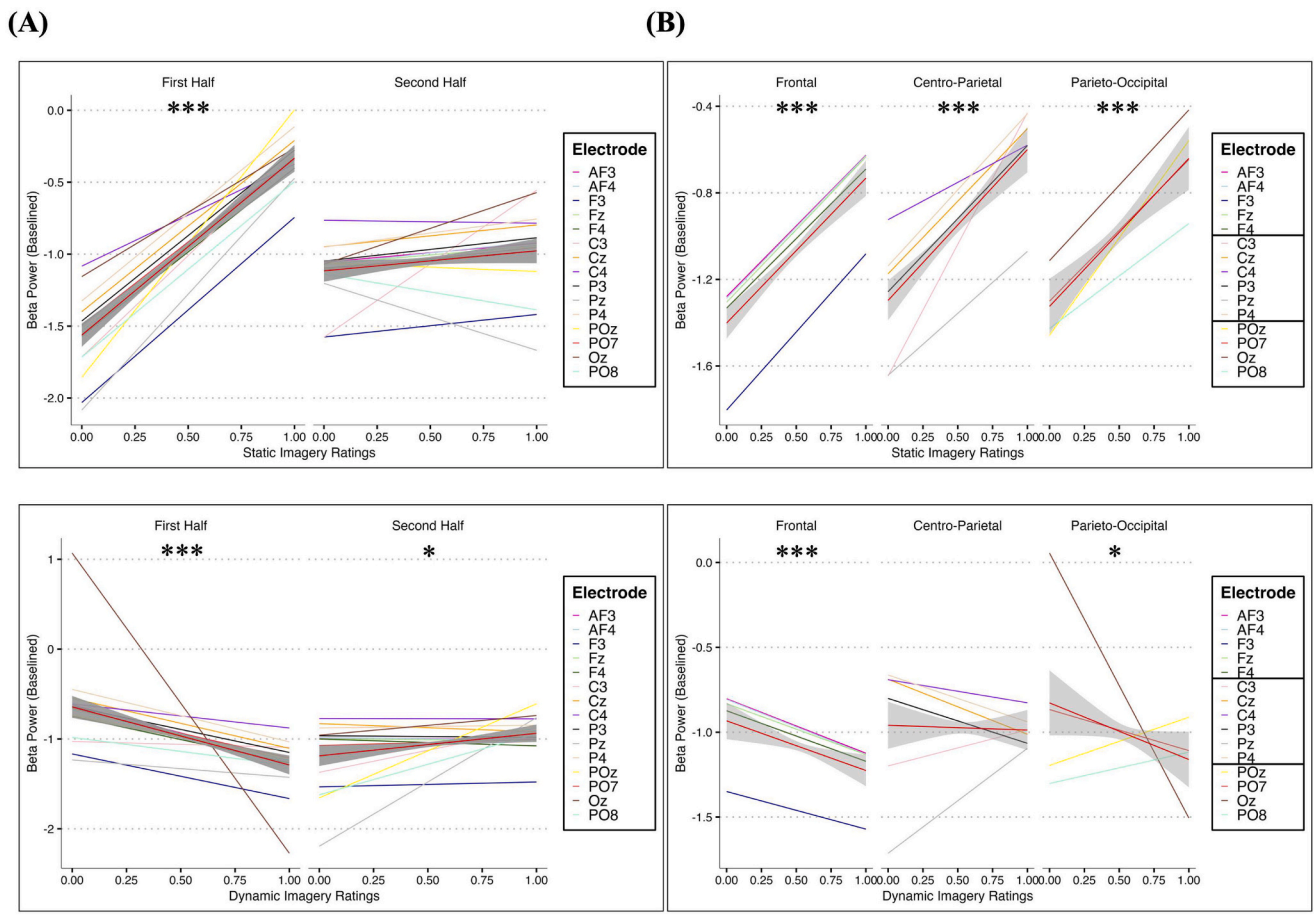
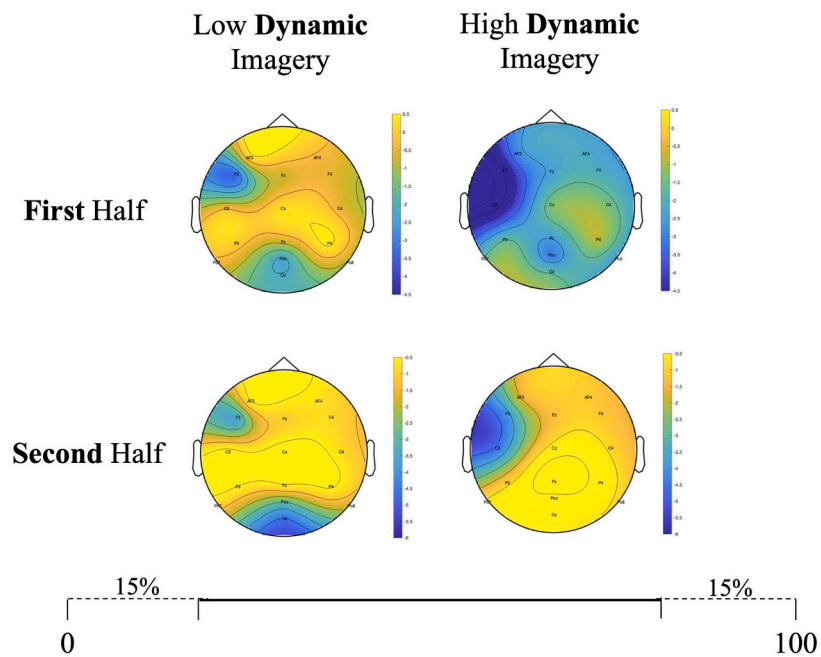


Fig. 3. Alpha power associated with static and dynamic imagery. Asterisks denote model significance levels: n.s. = non-significant, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. (A) Scatterplots showing alpha power as a function of static and dynamic imagery ratings, once the other had been regressed out, for two different time windows (First Half and Second Half). For illustrative purposes, the x-axis is scaled to between 0 and 1. Individual electrodes are represented by different colours. Thick red lines illustrate aggregated mean electrode power values, with shaded 95 % confidence interval. (B) Scatterplots showing alpha power as a function of imagery ratings, once the other rating had been regressed out, for three regions of interest (Frontal: AF3, AF4, F3, Fz, and F4; Centro-Parietal: C3, Cz, C4, P3, Pz, and P4; and Parieto-Occipital: POz, PO7, Oz, and PO8). For illustrative purposes, the x-axis is scaled to between 0 and 1. Individual electrodes are represented by different colours. Thick red lines illustrate aggregated mean electrode power values, with shaded 95 % confidence interval. (C) For illustrative purposes, we present topoplots showing patterns of alpha power (baselined to 2 s prior to the music) from trials associated with the upper 10 % (denoted High) and lower 10 % (denoted Low) of static and dynamic imagery ratings for the first half only. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



(C)



(caption on next page)

Fig. 4. Beta power associated with static and dynamic imagery. Asterisks denote model significance levels: * $p < 0.05$, *** $p < 0.001$. (A) Scatterplots showing beta power as a function of static and dynamic imagery ratings, once the other had been regressed out, for two different time windows (First Half and Second Half). For illustrative purposes, the x-axis is scaled to between 0 and 1. Individual electrodes are represented by different colours. Thick red lines illustrate aggregated mean electrode power values, with shaded 95 % confidence interval. (B) Scatterplots showing beta power as a function of imagery ratings, once the other rating had been regressed out, for three regions of interest (Frontal: AF3, AF4, F3, Fz, and F4; Centro-Parietal: C3, Cz, C4, P3, Pz, and P4; and Parieto-Occipital: POz, PO7, Oz, and PO8). For illustrative purposes, the x-axis is scaled to between 0 and 1. Individual electrodes are represented by different colours. Thick red lines illustrate aggregated mean electrode power values, with shaded 95 % confidence interval. (C) For illustrative purposes, we present topoplots showing patterns of beta power (baselined to 2 s prior to the music) from trials associated with the upper 15 % (denoted High) and lower 15 % (denoted Low) of dynamic imagery ratings across the two different time windows. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

dynamic ratings was, similarly to the overall alpha band, significant in both lower and upper alpha, a frontal alpha suppression effect for static ratings – that was not seen in the overall or lower alpha model – was found when considering upper alpha alone.

In sum, the findings suggest that parieto-occipital lower alpha may be similarly involved in both visual imagery types but that differences between lower and upper alpha may reflect separate functionalities of static and dynamic imagery. See Figs. S3 and S4 for visualisations of these results.

3.5. Exploratory analyses: effects of musicianship

There is little neuroscientific research concerning the relationship between musical training and visual imagery, though some behavioural investigations suggest that training enhances the vividness of music-induced visual imagery (Küssner and Eerola, 2019), enables faster visual imagery formation through improved sensorimotor integration (Brochard et al., 2004), and leads to mental rehearsal of motor performance through kinaesthetic imagery (Lotze, 2013). EEG research shows that musical training improves the coactivation of auditory and sensorimotor processes in anterior brain areas (Bangert and Altenmüller, 2003; Klein et al., 2015; Trainor et al., 2009). In a final set of exploratory analyses, we therefore examined the influence that musical training scores may have on the patterns of neural activity that accompany visual imagery (see Supplementary Materials for a detailed outline of the results).

In brief, we observed, with regard to alpha power and static imagery, that those with more musical training showed the suppression effect (in the first time window) to a greater extent than those with less training (although the rebound in the second was greater for those with less training). Interestingly, with regard to alpha and dynamic imagery, less trained participants showed the alpha suppression effect more in the first time window while more trained showed it to a greater extent in the second time window.

Further, while beta in response to static imagery did not show much difference between the two musicianship groups, the beta suppression effect in response to dynamic imagery (in the first time window) was greater in less trained than trained individuals. Finally, with regard to gamma, it was seen that the previously reported positive relationship between gamma and dynamic imagery was driven particularly by those with low training.

4. Discussion

Behavioural studies have demonstrated music's propensity to elicit visual imagery (Baltes and Miu, 2014; Hashim et al., 2020; Juslin, 2013; Juslin and Västfjäll, 2008; Küssner and Eerola, 2019; Taruffi and Küssner, 2019, 2022) that varies in terms of dynamicity (Eitan and Granot, 2006; Johnson and Larson, 2003). The aim of the current study was to examine the neural signatures of music-induced visual imagery and to determine the extent to which static and dynamic imagery can be seen reflected in differing patterns of neural oscillations.

Based on literature implicating the modulation of different frequency bands in the visual and motor brain regions in response to static and dynamic imagery (De Lange et al., 2008; Fachner et al., 2019; Luft et al., 2019; Menicucci et al., 2020; Neuper and Pfurtscheller, 1996), we

explored three oscillatory bands (alpha, beta, and gamma) in three main brain regions of interest (Frontal, Centro-Parietal, and Parieto-Occipital). Further, based on preliminary evidence regarding the time-frame within which music-induced visual imagery can occur (Day and Thompson, 2019), we also considered how patterns of activity differ in the first (by which point visual imagery has likely occurred) and second halves of the thirty-second listening experience.

First, in line with the notion that visual imagery recruits similar brain areas and mechanisms to visual perception, we predicted that both static and dynamic visual imagery ratings would show a negative relationship with alpha as well as (particularly for dynamic imagery) a positive relationship with gamma in the parieto-occipital region (De Lange et al., 2008; Fachner et al., 2019; Lehmann et al., 2001; Luft et al., 2019; Sepúlveda et al., 2014). We further predicted that dynamic imagery, due to its recruitment of motor areas of the brain, would be associated with potentially complex patterns of beta desynchronisation and synchronisation (Menicucci et al., 2020; Neuper and Pfurtscheller, 1996; Salmelin et al., 1995; Villena-González et al., 2018; Zabielska-Mendyk et al., 2018).

4.1. Posterior alpha suppression during visual imagery

In line with past literature that has found strong links between visual imagery generation and occipital alpha activity (Cooper et al., 2003; Fachner et al., 2019; Schaefer et al., 2011, 2013), we found evidence for parieto-occipital alpha suppression as a function of visual imagery, although this suppression effect with regard to time period more specifically was only present in the first half of the piece for both imagery types (i.e., within the 12 s period by which visual imagery is held to occur; Day and Thompson, 2019) and, for static imagery, even turned to an enhancement effect in the second half of the listening experience.

Here, we speculate that the ratings-related alpha suppression effect was limited to the earlier time window due to visual imagery having already emerged (or not) within this 12 s period (whether due to the affordances of the stimuli or even deliberate action on the part of the listener). Indeed, it is possible that this earlier period is what listeners base their imagery ratings on. In turn, we speculate that the consequent positive relationship between alpha power and static imagery ratings seen in the second half may reflect a rebound (increase) in alpha levels that is commensurate with the initial drop seen in the first half.

The visual imagery ratings and alpha relationships in the second half of the listening experience are interesting as they likely reflect the intrinsic difference between music-induced static and dynamic visual imagery. Indeed, while we did not make this explicit prediction, it is possible that (in contrast to the tendency for alpha levels to show a rebound effect in the second half of the listening experience with respect to static imagery ratings) dynamic imagery ratings do not show an alpha rebound effect because dynamic imagery is constantly changing over the course of the listening experience and thus keeps alpha levels low (potentially at floor levels).

Here, it is, however, important to note that the low temporal resolution of the ratings prevents us from drawing detailed conclusions on the differences between static and dynamic imagery, and thus remains a key limitation of the current research. The current design, whereby ratings are provided only after each listening trial, fails to provide information on the dynamics of the prevalence and magnitude of visual

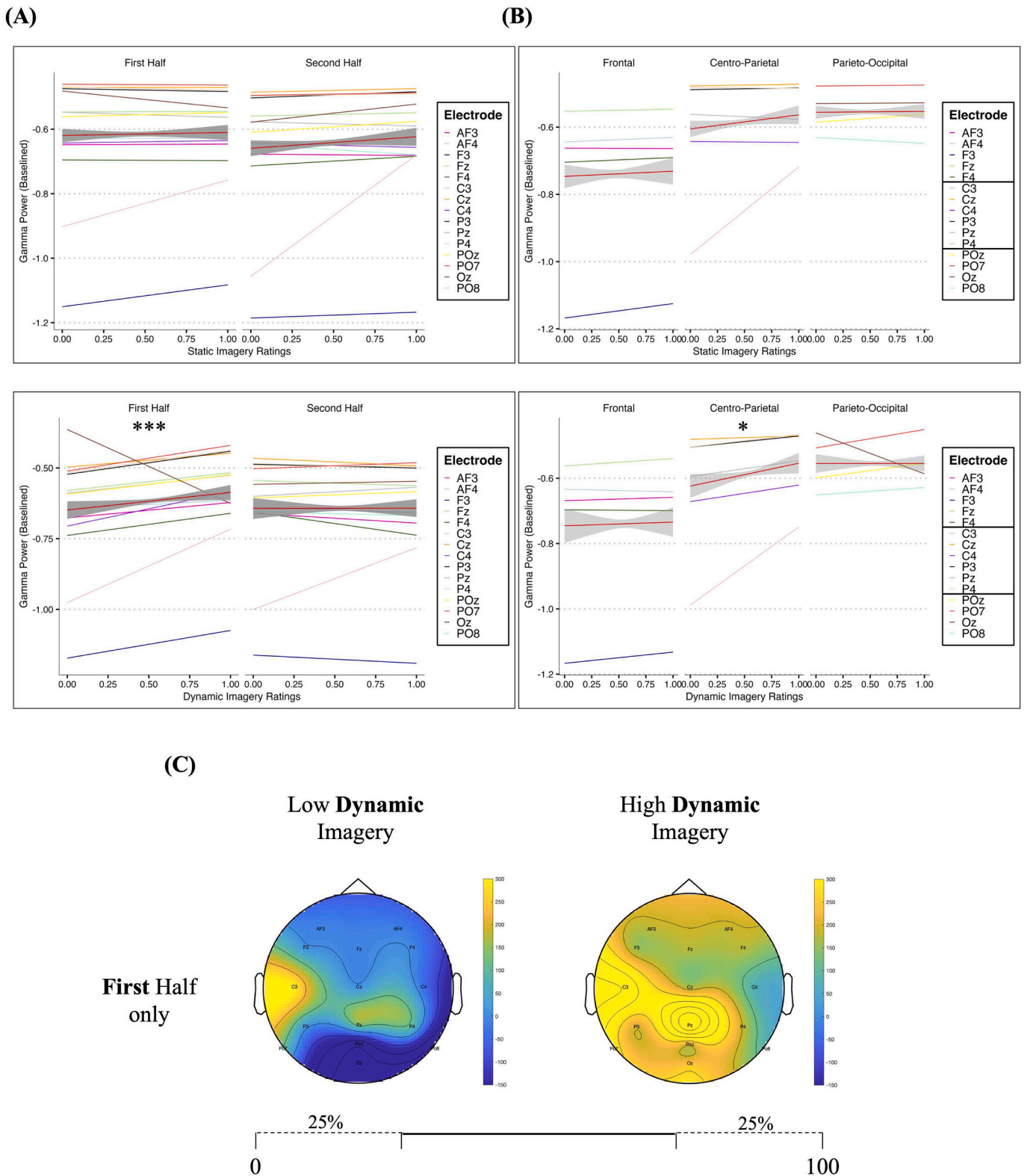


Fig. 5. Gamma power associated with static and dynamic imagery. Asterisks denote model significance levels: * $p < 0.05$, *** $p < 0.001$. (A) Scatterplots showing gamma power as a function of static and dynamic imagery ratings, once the other had been regressed out, for two different time windows (First Half and Second Half). For illustrative purposes, the x-axis is scaled between 0 and 1. Individual electrodes are represented by different colours. Thick red lines illustrate aggregated mean electrode power values, with shaded 95% confidence interval. (B) Scatterplots showing gamma power as a function of imagery ratings, once the other rating had been regressed out, for three regions of interest (Frontal: AF3, AF4, F3, Fz, and F4; Centro-Parietal: C3, Cz, C4, P3, Pz, and P4; and Parieto-Occipital: POz, PO7, Oz, and PO8). For illustrative purposes, the x-axis is scaled to between 0 and 1. Individual electrodes are represented by different colours. Thick red lines illustrate aggregated mean electrode power values, with shaded 95% confidence interval. (C) For illustrative purposes, we present topoplots showing patterns of gamma power (baselined to 2 s prior to the music) from trials associated with the upper 25% (denoted High) and lower 25% (denoted Low) of dynamic imagery ratings for the first half only. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

imagery over the course of a music excerpt. Thus, our conclusions remain speculative, and further studies would greatly benefit from designs that enable the experience of visual imagery to be collected over time. Such designs would allow the neural correlates of static and dynamic imagery to be more carefully disentangled and would also throw light on how different types of imagery may be induced by different acoustic features.

4.2. Dynamic imagery associated with different patterns of activity from static imagery

We predicted that dynamic imagery would be similar to static imagery in terms of posterior alpha suppression but potentially more notably associated with gamma enhancement than static imagery. These predictions proved to be mostly accurate. In terms of posterior alpha suppression, we observed that dynamic imagery was associated with alpha suppression although unlike static imagery, dynamic imagery was not associated with a tendency to return to original alpha levels over the course of the imagery experience.

In terms of gamma activity, only dynamic imagery showed parieto-occipital gamma enhancement (De Lange et al., 2008). This difference found between dynamic and static imagery with respect to gamma oscillations is in line with past assertions that gamma oscillations are most evident when imagery is complex (De Lange et al., 2008; Sepúlveda et al., 2014), as can be assumed for more dynamic forms of imagery content.

Furthermore, with regard to additional differences between dynamic and static imagery, we predicted that dynamic imagery may be associated with both synchronisation and desynchronisation of beta frequency band in frontal, centro-parietal, and parieto-occipital areas. Indeed, here we showed that dynamic imagery was associated with a suppression (desynchronisation) in all regions of interest followed by an enhancement (synchronisation) of beta power in the parieto-occipital area specifically; this is in contrast to static imagery which was associated with beta enhancement in the first time period only and across all regions of interest. In line with previous results, we suggest that the beta suppression seen with dynamic imagery in the first 15-s time window reflects the recruitment of motor regions (Menicucci et al., 2020; Zabielska-Mendyk et al., 2018) and that the subsequent enhancement reflects the rebound in beta that has been reported to occur following such motor activity (Neuper and Pfurtscheller, 1996; Salmelin et al., 1995).

With regard to the unexpected beta enhancement seen as a function of static imagery ratings in the first time period, we propose – as has previously been suggested – that this may reflect the cross-modal processing of visual and auditory information simultaneously (Villena-González et al., 2018). As dynamic imagery is just as likely to involve such cross-modal processing, it is important to put forward the possibility that – along with any beta power rebound effect (Neuper and Pfurtscheller, 1996; Salmelin et al., 1995) – such cross-modal processing also drives the positive relationship between beta and dynamic imagery that is seen in the second time period.

Finally, it is important to note that unlike static imagery, dynamic imagery was associated with robust frontal alpha suppression. Previous work has shown dynamic imagery to be associated with greater frontal alpha power when compared to static imagery (Sousa et al., 2017); and others have suggested that this may be due to the higher internal processing demands and task complexity (Cooper et al., 2003; Klimesch et al., 2007; Sauseng et al., 2005; Schomer and da Silva, 2012) of dynamic imagery compared to static imagery. Even though our findings seem opposed to those from Sousa et al. (2017), it is important to note that a direct comparison with their work is difficult since their study compared two different conditions (static and dynamic), whereas we measured static and dynamic imagery using subjective ratings for each. Further work is needed to corroborate our finding of frontal alpha suppression in response to dynamic content of visual imagery.

An additional exploration involved examining potential differences between lower and upper alpha in their associations with static and dynamic imagery. The results demonstrated minimal differences between overall alpha power and lower alpha power with regard to power suppression in response to static and dynamic imagery, suggesting that the lower band may be an effective reflection of both types of visual imagery content. The findings nevertheless also show that certain effects may be present in upper but not lower alpha (e.g., frontal alpha suppression in response to static ratings) thus suggesting that these sub-bands may indeed play distinct roles. Taken together, our findings support past literature proposing distinct functions of lower and upper alpha power (Petsche et al., 1997).

Our final exploration involved examining the influence of musical training on the relationship between oscillatory power and visual imagery ratings. Though findings in previous research have been mixed (Aleman et al., 2000; Küssner and Eerola, 2019), patterns of results suggest that musical training influenced patterns of neural activity in nuanced ways. The differences in patterns of oscillatory activity – during visual imagery – that one should expect when considering how the musically trained brain differs from the typical brain is not yet well documented. Further studies are therefore needed to understand this potential influence of musical training on neural substrates of music-induced visual imagery.

In summary, our results present a few unexpected differences between static and dynamic imagery with respect to alpha modulation but are in line with our predictions that i) both imagery types would drive posterior alpha suppression, ii) the two may show different effects over time (due to dynamic but not static imagery being associated with continuous changing imagery content), and iii) dynamic imagery, to a greater extent than static imagery, would show complex modulation of areas involved in motion processing (Sirigu and Duhamel, 2001; Thompson et al., 2009; Zacks, 2008).

4.3. Implications of the research

We provide preliminary evidence to show that the neural correlates of music-induced visual imagery may include both posterior alpha suppression, and beta and gamma modulation. This research adds to similar previous research by Fachner et al. (2019) who also showed evidence of posterior alpha suppression but did not investigate gamma power. As such, our study highlights the fact that music is a powerful tool to study the neural correlates of visual imagery. Further, the consistency of our findings with the previous body of work on visual motor imagery can be taken as support for the idea that motion plays a significant role in music-induced visual imagery (Antović et al., 2024; Dahl et al., 2022) and, as such, in the music listening experience more generally (Eitan and Granot, 2006; Johnson and Larson, 2003; Schaefer, 2014).

However, perhaps the most important implication of our research relates to future investigations of the neural correlates of dynamic visual imagery. Indeed, this literature, much of which has focused on athletes (Wilson et al., 2016) or used small samples to explore brain-computer interfaces (Sousa et al., 2017), offers mixed results as to the directionality and cortical localisation of effects related to the experience of dynamic or motion-related imagery. Our findings, which are in line with the results of a meta-analysis suggesting a great overlap between visual motor imagery and kinaesthetic motor imagery (Filgueiras et al., 2018), suggest that music-induced visual imagery could be particularly useful for future studies seeking to explore dynamic content of visual imagery.

That said, it is important to consider the possibility that studies using musical stimuli show neural effects that not only reflect visual imagery content but also features of the music that induce said imagery content. Here, we sought to account for the effects of music heard (on the differing brain signatures we reported for static and dynamic imagery) by including the musical pieces as random effects within our mixed modelling analysis approach. However, preliminary findings of the

effects that musical features can have on visual imagery (Dahl et al., 2022; Herff et al., 2022; Juslin, 2019) suggest that future studies may want to control for such variables even more carefully.

Relatedly, past behavioural studies have reported high prevalence rates of visual imagery during music (Dahl et al., 2022; Küssner and Eerola, 2019; Vuoskoski and Eerola, 2015), leading us to view it as a useful reliable stimulus. However, a relevant concern is that insights from studying music may not all be generalisable to other instances of static and dynamic imagery. Here, we suggest that while some neural patterns may relate specifically to music's acoustic properties, this is the case for all other stimulus types that may be used for inducing imagery. Further, even though we pointed out that music-induced visual imagery has been related to music's aesthetic appeal (Belfi, 2019), differing levels of aesthetic evaluation to differing imagery content is something that would be present in other imagery induction paradigms, including simpler paradigms where people are asked to imagine different scenes in the absence of any inducer. Future studies where such additional factors are a potential concern could seek to track such variables and account for them in the analysis approach.

As previously mentioned, future investigations should further seek to corroborate and extend our results by using alternative experimental designs that enable explicit comparison between music-induced static and dynamic visual imagery. While the current study touches upon partially distinct processes that may underpin these two types of visual imagery, such further studies will be valuable.

5. Conclusion

We aimed to further our understanding of the oscillatory characteristics underlying two types of visual imagery content during music listening: static and dynamic. In line with our predictions, we corroborated past literature on the oscillatory signatures of visual imagery and reveal nuanced differences in signatures of static and dynamic content of visual imagery. Investigations into what listeners tend to imagine whilst listening to music is gaining traction. Our study opens further avenues into the operationalisation of commonly occurring forms of visual imagery and into the examination of how they can be observed in neural data.

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Ethical approval

Ethical approval (Ref. 2017-32) for this research was granted by the Ethics Committee of the Institute of Psychology at Humboldt-Universität zu Berlin, Germany.

Consent to participate

All participants provided written consent to be included in this study and were given monetary compensation or course credit for their time.

CRediT authorship contribution statement

Sarah Hashim: Formal analysis, Visualization, Writing – original draft, Writing – review & editing. **Mats B. Küssner:** Conceptualization, Investigation, Methodology, Supervision, Writing – review & editing. **André Weinreich:** Conceptualization, Investigation, Methodology, Writing – review & editing. **Diana Omigie:** Formal analysis, Supervision, Writing – review & editing.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ijpsycho.2024.112309>.

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